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DEVELOPMENT AND APPLICATION OF A PROCEDURE TO ESTIMATE OVERALL BUILDING AND VENTILATION PARAMETERS FROM MONITORED COMMERCIAL BUILDING ENERGY USE

A Thesis

by

SONG DENG

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 1997

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Approved as to style and content by:

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ABSTRACT

Development and Application of a Procedure to Estimate Overall Building and Ventilation Parameters from Monitored Commercial Building Energy Use.

(May 1997)

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This thesis proposes and validates a simplified model appropriate for parameter identification and evaluates several different inverse parameter identification schemes suitable for use when heating and cooling data from a commercial building are available. The validation has been performed using such data generated from a detailed building simulation program for different building geometries and building mass levels in two different climatic locations. Such a synthetic evaluation will validate the model used as well as determine the best parameter identification scheme, i.e., one likely to yield the most accurate set of parameter estimates.

A multistep identification scheme has been found to yield very accurate results, and a more careful evaluation has been performed in order to evaluate its accuracy and stability with synthetic data against the effects of solar energy, HVAC system operation, internal load schedule, building thermal mass and geometry, and climatic

location. This method is also evaluated using data from different time periods and when utility bill data (i.e. monthly data) only is available.

The model is then applied to energy use data from two buildings being monitored under the Texas LoanSTAR Program, which are in different locations and have different HVAC systems. With parameters thus determined, two energy use indices, Energy Delivery Efficiency (EDE) and Multizone Efficiency Index (MEI), are calculated to present some insights into the benefits of retrofit from a constant volume (CV) to a variable air volume (VAV) system and of continuous commissioning (CC) work done to these two buildings, respectively. Uses and limitations of EDE and MEI are also discussed.

Based on these findings, it is suggested that the multistep regression approach is an accurate and practical building physical parameter determination method, and the combined use of the EDE and MEI indices calculated from these parameters can provide insights into the HVAC system, and the potential for optimizing its operation.

DEDICATION

To my parents, Jiuru Deng and Huimin C. Deng, my sister, Bing Deng, and my brother Chi Deng, whose love accompanies me anywhere in this world.

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NOMENCLATURE

A	Conditioned floor area of building
A_S	Surface area of building
c_p	Specific heat at constant pressure
E	Whole-building HVAC system energy use or load
h_V	Heat of vaporization
k_l	Ratio of internal latent loads to total internal sensible loads of building
k_s	Multiplicative factor for converting q_{LR} to total internal sensible loads
m_v	Ventilation air flow rate per unit conditioned area
Q_B	Building thermal loads
q_{LR}	Monitored electricity use area of lights and receptacles inside the building per unit
T	Outdoor temperature
U	Overall building shell heat loss coefficient
w	Specific humidity

Subscripts

B	building
C	cooling

c	constant volume (CV) system
H	heating
Ideal	ideal
m	Hourly Analysis Program (HAP) program simulated
min	minimum
o	outdoor
pre	pre
post	post
simu	simulation
sol	solar
v	ventilation
v	variable air volume (VAV) system
z	zone

Greek

δ	indicator variable in eq. (3.2)

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CHAPTER I

INTRODUCTION

1.1 Background

The United States consumes 82 quads of energy per year of which 34 quads are in existing buildings. Commercial buildings consume 13 quads, the remainder being in residential buildings. Since most buildings were constructed when energy was inexpensive, at least 30% of the energy use in the buildings sector is wasted due to inefficient equipment and operation (Bevington and Rosenfeld, 1990). In attempting to develop effective HVAC systems for new and existing buildings, mechanical and electrical engineers coined terms, such as "energy management program" and "energy audit" which have begun to catch the attention of the management community. Currently each year some 2% of commercial buildings undergo a major retrofit (Brambley, 1988). In the Texas LoanSTAR program a 24% energy consumption reduction was measured in 64 commercial buildings where retrofits with an average payback of 3 years were performed (Claridge, 1994). This implies an awesome opportunity for city planners, architects and engineers: It is not too late to make existing buildings better.

This thesis follows the style and format of *ASHRAE Transactions*.

From the building owner's viewpoint, energy conservation efforts must pay off on the bottom line and likewise, they need to know which buildings to target for potential energy savings. Traditional on-site energy audits that are performed to identify specific energy consuming systems which need retrofits tend to be expensive; they can even be a waste of money if the building owner does not eventually implement part of or all of the recommendations. If retrofit opportunities can be guided by building energy consumption data analysis, time and money will be saved. In fact, energy consumption data can reveal building HVAC system operation conditions, if effective and accurate diagnostic techniques are available.

1.2 Texas LoanSTAR Program

The Texas LoanSTAR Program is a $ 98.6 million revolving loan program to retrofit state owned buildings. It is funded by the Texas Governor's Energy Office using oil overcharge dollars. The money is used to retrofit state, local government and school buildings in Texas. The participants in the program were initially required to repay the loan and interest in four years or less according to audit estimated savings. However, larger repayment periods are now possible for retrofits with payback periods up to eight years. As part of the program, a state-wide Monitoring and Analysis Program (MAP) was set up in 1989. The main purposes of the MAP are to measure savings resulting from the energy conserving retrofits, to use the monitored data to diagnose opportunities for more efficient operation, and to establish a state-wide end-use data base (Turner, 1990).

Use of diagnostic techniques with the monitored data is a crucial aspect of the Texas LoanSTAR Program. Accurate diagnostic techniques which assess the success of the program are powerful tools for continuation and implementation of retrofits and continuous commissioning in additional buildings. They can also help improve future retrofit and CC measure selection. In addition, metered data analysis has also been found to provide insights in improving the efficiency of building HVAC system operation.

1.3 Objective and Purpose

The purpose of this thesis is to describe the development of a method for determining whole-building physical parameters from non-intrusive monitoring of heating and cooling energy use of large commercial buildings and apply this to data from actual buildings.

The objectives of this thesis are to: i) describe an index, called Energy Delivery Efficiency (EDE), ii) develop a multistep linear regression approach to identify physical parameters affecting the EDE, and iii) evaluate this approach with energy use data obtained from building simulations and from real monitored buildings.

The chapters that follow, will review the literature on methods for analyzing monitored energy use and parameter identification, describe the theoretical basis of the EDE concept, present a simplified model for building energy use, evaluate several different parameter estimation methods, and apply the best estimation process to several institutional buildings monitored by the Texas LoanSTAR program. Results are then summarized, followed by discussion and conclusions.

CHAPTER II

ANALYSIS OF MEASURED BUILDING ENERGY DATA - LITERATURE REVIEW

Energy analysis plays an important role in developing an optimum HVAC and architecture design for new buildings and in determining cost effective modifications to existing buildings. One classification scheme for energy analysis methods was proposed by Rabl et al. (1986), which divides building energy analysis into forward, inverse, and hybrid modeling schemes (Rabl et al., 1986; Rabl, 1988). The following text presents a brief background of existing energy analysis methods using Rabl's classification to provide the foundation for understanding and implementing the multistep regression method developed in this thesis.

2.1 Methods for Thermal Analysis of Buildings

At the design stage, the performance of a building needs to be calculated, based on its detailed description (blueprint). This is an instance of what is sometimes called the forward problem, by contrast to the inverse problem where performance data are available and the building description needs to be deduced (Rabl, 1988). Forward methods for thermal analysis of buildings, such as to calculate the energy performance of a prospective building or sizing the equipment to be installed in a new building for design purposes, fall into two major groups, steady-state methods (based on degree-days or temperature bins) and dynamic methods (e.g., based on transfer functions).

2.1.1 Forward Steady-State Methods

The traditional degree day method (ASHRAE, 1987) for estimating heating energy requirements is based on the assumption that, on a long term average, solar and internal gains will offset heat loss when the mean daily outdoor temperature is 65 °F, which is called balance point temperature, and that energy consumption will be proportional to the difference between the mean daily temperature and 65 °F. The applicability of this method is limited to residential buildings, where the envelope transmission and infiltration are the dominating factors contributing to the building load. For commercial buildings with highly varying internal loads and complicated HVAC systems, this method is not adequate. Also in response to the fuel crises of the 1970s, heat transmission coefficients have been reduced, and thermostat setback has become a common practice. At the same time the energy use by appliances has increased. These trends reduce T_{bal}, and evidence for this has been found by Fels and Goldberg (1986).

The basic approach for an improved degree day method is to permit a variable balance point temperature, whose value depends on the thermal parameters of the building and its gains. In this way, the degree day method has a variable base. So the variable-base degree day (VBDD) method is a generalization of the degree day method. It retains the familiar degree day concept, but counts degree days based on the balance point temperature, defined as the average outdoor temperature at which the building requires neither heating nor cooling. The VBDD concept has considerable flexibility, since cooling or heating energy load can be calculated for periods as short as a few days and as long as a season (Alereza and Hovander, 1981; Kusuda et al., 1981).

There are many applications where the degree day method should not be used, even with variable base: examples include situations where the heat loss coefficient and the efficiency of the HVAC system, or the balance-point temperature may not be sufficiently constant. In such cases, a steady-state calculation can yield good results for the annual energy consumption, if different temperature intervals and time periods are evaluated separately. This approach is called the bin method, because the consumption is calculated for several values of the outdoor temperature and multiplied by the number of hours in the temperature interval (= bin) centered on that temperature (Rabl, 1988). In the United States, the necessary data, called bin data, are widely available in temperature intervals of 5 °F. By using the bin data for the corresponding periods, the calculation can take the operating schedules of commercial buildings into account and make the result more accurate.

2.1.2 Forward Dynamic Methods

As previously mentioned, forward steady-state methods for energy consumption are most accurate when the indoor temperature is constant. However, in many buildings indoor temperature can vary from thermostat setback and setup. In passive solar buildings, indoor temperature varies even when thermostat setpoint is constant (Rabl, 1988). In these cases, an uncorrected steady-state method should not be used. Several shorthand methods have been developed that include correction terms for variable indoor temperature. However, the introduction of dynamic correction terms tends to spoil the simplicity of the steady-state approach. On the other hand, with the evolution of computer technology, dynamic calculations have become much easier and generally accepted. The principles of a dynamic calculation of energy consumption are the same as a dynamic calculation of peak loads, and the calculation is simply repeated, time step by time step, for the entire year, including the efficiency of the HVAC equipment as appropriate. For an annual energy calculation, hourly weather data for each day of the year are used instead of a sequence of identical days. This procedure is realized in the DOE2.1 computer simulation program (Birdsall et al., 1990).

2.2 Methods for Analyzing Measured Building Energy Data

The above forward methods just described are most often employed for design purposes. On the other hand, analyzing measured building energy data is a crucial aspect of any conservation program, which makes the continuation and implementation of cost effective retrofits in additional buildings more likely and can improve selection of future retrofit measures.

Current effort by ASHRAE GPC 14P which is developing consensus guidelines for the measurement of energy and demand savings for residential, commercial, and industrial cost reduction retrofits, focuses on the relationship of the measurement to the equipment being verified. In a related effort the North American Energy Measurement and Verification Protocol (NEMVP) (DOE, 1996) discusses a variety of measurement and verification (M&V) topics as they relate to actual contracts for energy services. Both ASHRAE GPC 14P and the NEMVP discuss methods for analyzing measured building energy data, in order to accurately calculate savings of retrofits. To determine energy savings, the parties (the building owner, the installer and perhaps the financer) must first agree on the "base line" (what the building used before retrofit), and then must measure energy use after retrofit (DOE, 1996). In the NEMVP, baseline energy use, post-installation energy use and energy (and cost) savings can be determined using one or more of the following M&V techniques:

- Engineering Calculations
- Metering and Monitoring
- Utility Meter Billing Analysis

Three principal methods for analyzing measured building energy data will be discussed below, including the empirical model approach, calibrated simulation and parameter identification using macro-models.

2.2.1 Empirical Regression Model Approach

The regression model analysis method is empirical which means the energy use is statistically determined as a function of one or more driving forces which affect the building. This is also known as inverse or data-driven modeling because the calculation scheme is performed in a backward or inverse fashion (i.e. the measured energy data are statistically analyzed to infer the values of the model parameters which describe the building's performance).

The simplest method used to measure energy savings is the direct comparison of the pre-retrofit and post-retrofit energy use, usually on a monthly basis. However, varying weather conditions between the pre-retrofit and post-retrofit periods can influence energy use and obscure the change in the energy use caused by the retrofit. The weather corrected savings can differ by up to 12% from uncorrected savings (Greely et al., 1990). This would indicate that saving calculations that are based on direct comparisons should only be used for retrofits that are estimated to save substantially more than 12% of the annual energy use.

When the energy use data are weather normalized, the weather effect is normally analyzed using one or more weather parameters as independent variable(s) for the analysis. This is the primary idea behind simple and multiple linear regression models. Some recent methodologies improve upon linear regression by adding a change-point, non-linearity to the regression. These include a three parameter change-point method (Fels and Goldberg, 1986; Fels et al., 1995) and the four-parameter change-point method by Ruch and Claridge (1992). In these models, a known physical building phenomena (such as heating cut-off point or balance point) is used to improve the statistical analysis and, thus, differentiate the models from simple-linear, two-parameter regression models. Another improvement, proposed by Ruch et al. (1993), handles collinearity in multiple regression using the principal component regression models.

Regression models are easier to develop than mechanistic models because of their simplicity, and repeatability. Regression models also benefit from a well-defined statistical theory and allow the calculation of the associated uncertainty (Neter et al., 1989).

2.2.2 Calibrated Simulation Model Approach

The calibrated simulation model approach is a hybrid modeling method, which contains characteristics of both the forward and inverse methods. One example of this is the use of engineering equations to simulate an existing building's energy consumption while using measured energy consumption data to determine various model coefficients or to calibrate the simulation. For retrofit savings determination, simulations are most often used where little or no baseline data are available. In such cases the calibrated model is based on post-retrofit energy use characteristics (Katipamula and Claridge, 1993).

The calibrated simulation approach is meant to be used in projects where reliable calibrated simulation models can be developed and used to measure savings. In this approach, a thermodynamic simulation model of a building's energy use is developed from engineering principles. Model predictions are calibrated by adjusting input parameters until model predictions closely match measured data from the building being modeled at the daily or hourly level. Examples include calibrated DOE-2 analysis (Haberl et al., 1993; Bou-Saada, 1994; Bou-Saada and Haberl, 1994; Haberl and Bou-Saada, 1995; Katipamula et al., 1995), calibrated simplified HVAC system models (Knebel, 1983; Katipamula and Claridge, 1993; Reddy et al., 1994). Calibrated modeling has also been used to identify operational improvements in buildings (Claridge et al., 1994).

2.2.3 Parameter Identification Using Macro-models

Parameter identification, or the "inverse method", is a well-known discipline which has been the subject of extensive research over the last three decades and has major applications, not only in the engineering sciences, but also in areas such as medicine and sociology (Beck and Arnold, 1977). Several books and innumerable journal articles and papers have been written on this subject (Sonderegger, 1978; Unbehauen and Rao, 1987; Subbarao, 1988; Rabl, 1988; Reddy, 1996). It makes use of additional information not available to the forward approach, viz. measured system performance data, to develop a macroscopic model that captures the major physical interactions of the data. This "fine tuning" makes the inverse approach suitable for diagnostics (i.e., analysis of system properties), predictions and optimal control, while the forward approach is more appropriate for design, sensitivity studies and system variation studies.

The process of identification or estimation involves the following steps (Unbehauen and Rao, 1987):

1. Write a mathematical model of the system containing unknown parameters. The model can be a simple algebraic expression in the case of steady-state lumped parameter modeling, or at the other extreme, a set of partial differential equations. The challenge is to formulate a model that captures all the essential primary physical interactions while leaving out the secondary effects.

2. Choose a method to solve the model. Regression, finite differencing, Laplace transforms or analytical approaches can be used as appropriate.

3. Design an optimal set of experiments. This involves deciding on a measurement protocol and the location of sensors in spatial and temporal domains. The experimental protocol is tied to the mathematical model used.

4. Choose a statistical criterion of model performance (for example, least squares, maximum likelihood principle, etc.)

5. Choose an optimization scheme (usually regression is used).

6. Perform a sensitivity analysis to gauge stability in the identification process.

7. Perform an error analysis using the chosen statistical criteria.

Intuitively, one would expect models identified by the inverse approach to be most realistic when experiments are carried out during normal operation of the system. Such an experimental protocol, known as non-intrusive or "on-line" or "on-time" identification, is not necessarily the best approach (Reddy, 1996). The driving forces may be too weak or repetitive in certain cases, even when several weeks of data are used for identification, to elicit a strong enough output signal for proper statistical treatment.

2.3 Building Energy Use Indices

Building energy use indices are valuable because they can provide insights that will help define CC measures or suggest HVAC recommendations to reduce energy use in the building. The multistep regression method developed in this thesis was applied to two well defined building energy use indices: Energy Delivery Efficiency (EDE) and Multizone Efficiency Index (MEI).

Reddy et al. (1994) proposed an index, called the Energy Delivery Efficiency (EDE), which characterizes the excess energy penalty due to multizone effects in commercial buildings and rates the energy performance of HVAC systems on an absolute scale (Reddy et al., 1994; Reddy et al., 1997). The approach is akin to the concept of Carnot Efficiency as a way of defining the theoretical limit of heat engines as well as rating the relative performance of different engines. Kreider and Rabl (1994) have proposed another index, namely the Multizone Efficiency Index (MEI), which accounts for the inefficiency caused by simultaneous heating and cooling of different zones, but retains the distinction between heating efficiency and cooling efficiency.

Both of these indices have benefits and limitations, and as findings of this thesis, they will be discussed in later chapters.

2.4 Summary

With the increased use of building energy analysis, a need exists for a simple but effective procedure to estimate overall building and ventilation parameters from monitored building energy use. Basing on these physical parameters, forward methods can be applied to estimate building energy use requirement very accurately. This will make the evaluation of building energy use indices (like EDE and MEI) possible; thus diagnostic analysis can follow.

From the above literature view, the best way to identify building and ventilation parameters is a regression approach using macro-models. Sonderegger's (1978) equivalent thermal parameter method (ETP) is an intrusive method which most concerns shell conduction from residential buildings. It is not quite applicable to non-intrusive measured energy use data of large commercial buildings where many building systems get involved. Subbarao's (1988) methods are more applicable to residential buildings, too. Rabl (1988) also worked on this topic, and he gave a general description of inverse methods for measured building energy use analysis. The example he used is for commercial buildings; however, the results are not very successful.

The proposed work in this thesis will develop and apply such an approach, combining the benefits of the inverse regression model with a variation of parameter identification techniques, to estimate building and ventilation parameters from non-intrusive monitoring of heating and cooling energy use of large commercial buildings. This procedure involves first deducing the loads of an ideal one-zone building from the monitored data and using a multistep linear regression approach to identify the physical parameters. The regression coefficients (along with their standard errors) thus determined can be directly used to deduce the required physical parameter coefficients (along with their standard errors). Simplicity and accuracy are two main characteristics of this procedure, and its successful application to two energy use indices, EDE and MEI, makes it more applicable for measured building energy use data analysis.

CHAPTER III

METHODOLOGY

3.1 Introduction

This chapter presents a new development which is part of an ongoing research effort to develop analysis techniques for non-intrusive continuously monitored whole-building heating, cooling and electricity use data in medium and large commercial buildings. This technique can help one ascertain whether (i) the HVAC system is functioning properly, and (ii) the extent to which the HVAC system is consuming more energy than an "ideal" HVAC system. Acquiring such insights will help define CC measures (i.e. HVAC recommendations to reduce energy use in the building).

The expressions for the "ideal" building loads contain certain terms for building and ventilation air effects. For our data analysis approach to be meaningful, it would be best to estimate these overall parameters from the monitored data itself. The inverse method is thus selected and the process of identification or estimation in the case of non-intrusive data collection (where controlled experiments cannot be performed on the system, as is our case) involves two major steps:

(a) Formulating a mathematical model of the system containing unknown parameters. The model could be anywhere from a simple algebraic expression, in the case of steady-state lumped-parameter modeling, or at the other extreme, a set of partial differential equations. The challenge is to formulate a model, which depending on the type of data available, (i) captures all the essential physical interactions while leaving out the secondary effects, and (ii) allows for the identification of all parameters explicitly (i.e., the model should not suffer from over-determination or under-determination).

(b) Selecting a statistical regression scheme which estimates the parameters so they have little or no bias. The scheme will have to minimize multi-collinearity effects among the various regressor variables as well as assure that the parameters are uniquely identified.

This chapter will first introduce the two building energy use analysis indices, EDE and MEI, and then present the simplified model appropriate for parameter identification which makes it possible to calculate these indices for real buildings. Then several different parameter estimation methods basing on this simplified model will be described and theoretically discussed. Evaluation and application of these methods will be presented in the following chapters.

3.2 Model Formulation

First, the basis of the EDE and MEI concepts and the expression for the ideal building loads will be briefly described. Taking the control volume to include both the HVAC system and the building, and viewing internal loads such as lighting to be generated inside the control volume, an instantaneous heat balance neglecting transient effects associated with thermal mass yields (Reddy et al., 1994):

$$Q_B = E_C - E_H \tag{3.1}$$

where

- Q_B - net building heat gains or net cooling load,
- E_C - measured whole-building cooling thermal energy supplied by the cooling coils, and
- E_H - measured whole-building thermal heating energy supplied by the heating coils.

The value (E_C - E_H) can be viewed as the amount of comfort energy which would be required had no mixing of cold and hot air streams taken place. This amount is, thus, a sort of absolute thermodynamic minimum. In reality, the building consumes total thermal energy amounting to ($E_C + E_H$).

The ideal HVAC system should only consume the required amount of energy necessary to offset the net building heat gains and to condition the minimum outdoor air intake stipulated by indoor air quality requirements. It is suggested to assume steady state operation and make the following assumptions :

(a) the thermostat set point temperature T_z is fixed at a mean yearly value;

(b) infiltration loads are assumed negligible or considered part of the ventilation loads;

(c) solar gains are a linear function of outdoor dry-bulb temperature (Vadon et al., 1991 and Knebel, 1983);

(d) no exhaust fans or vented lighting fixtures are assumed present;

(e) ducts are perfectly insulated (i.e., no heat losses) and ducts have no air leakage. Alternately, duct losses are considered to be part of envelope loads.

(f) no economizer cycle is present.

An expression for the total heat gains ($Q_{B,1\text{-zone}}$) of a one-zone space (i.e., a space where simultaneous heating and cooling does not occur) has been derived by Reddy et al. (1997) for both cases with and without a humidification subsystem. It is usually the electricity used by lights and receptacles inside a building which can be conveniently measured. In the absence of exhaust fans and vented lighting fixtures, this use, q_{LR}, appears as a portion of the total sensible internal loads. Heat gains from people consisting of both sensible and latent portions and other types of latent loads are not amenable to direct measurement and are, thus, usually estimated. Since the schedule of lights and equipment closely follows that of building occupancy, a convenient and logical manner to include the unmonitored sensible loads is to modify q_{LR} by a constant multiplicative correction factor k_S which accounts for the miscellaneous (i.e., unmeasurable) internal sensible loads. Also, a simple manner of treating internal latent loads is to introduce a constant multiplicative factor k_l defined as the ratio of internal latent load to the total internal sensible load ($k_s \cdot q_{LR}$) which appears <u>only</u> when outdoor specific humidity w_o is larger than that of the conditioned space. Assuming the sign convention that energy flows are positive for heat gains and vice versa, it was shown that when a humidification system is not present (Reddy et al., 1997),

$Q_{B,1\text{-zone}} =$ internal loads (sensible including gains from people) (a)

+ solar loads (both direct and transmission) (b)

+ shell transmission loads (c)

+ infiltration and ventilation loads (both sensible and latent) (d)

$$= q_{LR} k_s (1 + k_l \delta) A + a'_{sol} + (b_{sol} + UA_s + m_v A c_p)(T_0 - T_z)$$

$$+ m_v A h_v \delta (w_0 - w_z) \tag{3.2}$$

where,

a'_{sol} - the intercept of the linearized solar function.

b_{sol} - the slope coefficient of the linearized solar function,

A - building total floor area,

UA_s - building envelope coefficient,

m_v - ventilation flow rate,

and δ is an indicator variable which is 1 when $w_o > w_z$ and 0 otherwise. The effect of solar loads is linearized with outdoor temperature T_o (Vadon et al., 1991) and included in the terms a'_{sol} and b_{sol}.

Consequently, the EDE, which rates the amount of simultaneous heating and cooling, is defined as:

$$EDE_{1\text{-zone}} = \frac{\text{Thermodynamic minimum energy use}}{\text{Actual energy use}}$$

$$= \frac{(E_C - E_H)}{(E_C + E_H)} \tag{3.3}$$

$EDE_{1\text{-zone}}$ of an actual system, defined by eq. (3.3) and estimated from measured whole-building cooling energy and heating energy data, would lie between -1 and 1, the limits indicating no simultaneous heating and cooling. The building can then be viewed as operated at its thermodynamic efficiency limit.

Most commercial buildings have more than one zone. For the two-zone case, expressions for the EDE could be derived as follows (Reddy, et al., 1994):

$$EDE_{2\text{-zone}} = \frac{\text{Thermodynamic minimum energy use}}{\text{Actual energy use}}$$

$$= \frac{(E_{C,2-zone} - E_{H,2-zone})}{(E_{C,2-zone} + E_{H,2-zone})} \qquad (3.4)$$

And the ideal EDE could be expressed as:

$$EDE_{ideal,\ 2\text{-zone}} = \frac{\text{Thermodynamic minimum energy use}}{\text{Idealized minimum two-zone energy use}}$$

$$= \frac{\left(Q_{B,I} + Q_{B,E}\right)}{\left(\left|Q_{B,I}\right| + \left|Q_{B,E}\right|\right)} \qquad (3.5)$$

where

$Q_{B,I}$ - the thermal load on the interior zone, and

$Q_{B,E}$ - the thermal load on the exterior zone.

Negative values for EDE when $E_H > E_C$ can be avoided by taking absolute values of the numerators of the above equations. A more generalized form of eq. (3.5) is to rewrite it as:

$$EDE_{ideal,\ 2\text{-zone}} = \frac{\left(1 - Q_{B,E} / Q_{B,I}\right)}{\left(1 + Q_{B,E} / Q_{B,I}\right)} \quad T_{b,I} < T_a < T_{b,E} \qquad (3.6)$$

$$= \quad 1 \qquad\qquad \text{otherwise}$$

where, $\dfrac{Q_{B,E}}{Q_{B,I}} = (\dfrac{A_E}{A_I})(\dfrac{T_{b,E} - T_a}{T_a - T_{b,I}})(1 + \dfrac{UA_S + b_{sol}}{m_v c_p A_E})$ (3.7)

T_a - ambient temperature,

A_I - area of interior zone, and

A_E - area of exterior zone.

The balance point temperature for the interior zone is:

$$T_{b,I} = T_{set} - \frac{a_{int}}{m_v c_p} \tag{3.8}$$

where,

a_{int} - internal load (W/m^2).

The balance point temperature for the exterior zone is:

$$T_{b,E} = T_{set} - \frac{a_{int} A_E + a'_{sol}}{UA_S + b_{sol} + A_E m_v c_p} \tag{3.9}$$

$EDE_{ideal,\ 2\text{-zone}}$ is a function of the following parameters: T_a, a_{int}, A_I/A, UA_S/A and m_v.

$EDE_{2\text{-zone}}$ of an actual system, defined by eq. (3.4) and estimated from measured whole-building cooling energy and heating energy data, would be less than or equal to $EDE_{ideal,2\text{-zone}}$, the limit indicating no simultaneous heating and cooling. The building can then be viewed as operated at its thermodynamic efficiency limit. The expression for ideal two-zone buildings has been extended by Reddy et al. (1997) to include humidity effects and economizer cycles.

It is clear that EDE provides a measure of the energy efficiency of the HVAC system that combines both heating and cooling energy use. The Multizone Efficiency Index (MEI) accounts for the inefficiency caused by simultaneous heating and cooling of different zones wherein the distinction between heating efficiency and cooling efficiency is separately retained. Thus,

$$\text{Cooling MEI} = \frac{E_{C,\ ideal}}{E_{C,\ HVACsystem}} \tag{3.10a}$$

and

$$\text{Heating MEI} = \frac{E_{H,\ ideal}}{E_{H,\ HVACsystem}} \tag{3.10b}$$

It is convenient that both EDE and MEI indices could be defined at any time scale (daily, monthly, seasonally, and yearly). Application and discussion of these indices will be presented in chapter V to show the benefits and limitations of each.

3.3. Different Parameter Estimation Approaches

Instead of dealing with heating and cooling energy use separately, we shall consider $Q_{B,1\text{-zone}}$ with the understanding that positive values represent cooling loads and negative values denote heating loads. The expression for $Q_{B,1\text{-zone}}$ is given by eq. (3.2). If solar effects are neglected, there are six physical parameters to be estimated: k_s, k_l, UA_S, m_v, T_z and w_z. One can proceed to estimate these parameters in several ways.

3.3.1 One-Step Regression Approach

One way to identify these parameters is to directly resort to least-square multiple linear regression provided monitored data for q_{LR}, T_o and w_o is available. For such a scheme, it is more appropriate to rewrite eq. (3.2), neglecting solar loads, as:

$$Q_{B,1\text{-zone}}/A = a + b\cdot q_{LR} + c\cdot\delta\cdot q_{LR} + d\cdot T_o + e\cdot\delta\cdot(w_o - w_z) \qquad (3.11)$$

where the regression coefficients are:

$$a = -(UA_S/A + m_v \cdot c_p) \cdot T_z \qquad b = k_s \qquad c = k_s \cdot k_l$$

$$d = (UA_S/A + m_v \cdot c_p) \qquad e = m_v \cdot h_v \tag{3.12}$$

Subsequently, the physical parameters can be deduced from the regression coefficients as follows:

$$k_s = b \qquad k_l = c/b \qquad m_v = e/h_v$$

$$UA_S/A = d - e/(h_v \cdot c_p) \qquad T_z = a/d \tag{3.13}$$

The uncertainty associated with these physical parameters can be estimated from the classical equation for propagation of errors (ANSI/ASME, 1990). Let Δx represent the standard error of the regression coefficient x (a statistic which is provided by all statistical packages during regression). Then from eq. (3.13):

$$\Delta k_s = \Delta b$$

$$\Delta k_l = (c/b) \cdot [(\Delta c/c)^2 + (\Delta b/b)^2]^{0.5}$$

$$\Delta m_v = \Delta e/h_v$$

$$\Delta(UA_s/A) = [(\Delta d)^2 + (\Delta e/h_v/c_p)^2]^{0.5}$$

$$\Delta T_Z = (a/d)\cdot[(\Delta a/a)^2 + (\Delta d/d)^2]^{0.5} \qquad (3.14)$$

From the above five regression coefficients, parameters k_s, k_l, UA_S, m_v and T_z are easily deduced. The "best" value of building specific humidity w_z could be determined by a search method: select the value of w_z that yields the best goodness-of-fit to the data (i.e., highest R^2 or lowest CV-RMSE). Since w_z has a more or less well known range of variation, the search is not particularly difficult. Using year-long monitored data from two large commercial buildings in central Texas, it is found that the optimal value has a broad minimum in the range of 0.009 - 0.011 kg/kg. Thus, the choice of w_z is not a critical issue, and one could simply assume $w_z = 0.01$ kg/kg without much error in subsequently estimating other parameters.

3.3.2 Two-Step Regression Approach

The one-step regression approach described above is likely to suffer from a rather severe problem, namely collinearity effects between the regressor variables lead to improper parameter estimation. This phenomenon is well documented in the published literature (Reddy and Claridge, 1994). Daily data from several buildings in central Texas (like the Business building of the University of Texas at Arlington which is discussed in the next chapter) indicate that the variables (i) $(q_{LR}\cdot\delta)$ and T_o, (ii) $(q_{LR}\cdot\delta)$ and $\delta\cdot(w_o - w_z)$, and (iii) T_o and $\delta\cdot(w_o - w_z)$ are strongly correlated (correlation coefficients between variables are larger than 0.7) and are likely to introduce bias in the estimation of parameters from least-square regression. It is the last set of variables which is probably the primary cause of uncertainty in the parameter estimation process. Two-step regression involves separating the data set into two groups depending on $\delta = (w_o - w_z)^+$ being 0 or 1 (with w_z assumed to be 0.01 kg/kg). During the period when $\delta = 0$, eq. (3.11) reduces to

$$Q_{B,1\text{-}zone}/A = a + b\cdot q_{LR} + d\cdot T_o \qquad (3.15)$$

Since q_{LR} and T_o are usually poorly correlated, the coefficients b and d deduced from multiple linear regression are likely to be unbiased. For the remaining year-long data, i.e. when $\delta = 1$, eq. (3.2) can be re-written as:

$$Q_{B,1\text{-}zone}/A = a + (b + c)\cdot q_{LR} + d\cdot T_o + e\cdot\delta\cdot(w_o - w_z) \qquad (3.16)$$

Now, there are two ways of proceeding. One variant is to use eq. (3.16) as is, and determine coefficients a, (b+c), d and e from multiple regression. The previous values of a and d determined from eq. (3.15) are rejected, and the parameter b determined from eq. (3.15) along with those determined from eq. (3.16) are retained for deducing the physical parameters. This approach, termed two-step variant A, may, however, suffer from the collinearity effects between T_o and $\delta\cdot(w_o - w_z)$.

A second variant of the two-step approach, termed two-step variant B, would be to retain both coefficients b and d determined from eq. (3.15) and use the following modified equation to determine a, c and e:

$$Q_{B,1\text{-}zone}/A - d\cdot T_o = a + (b + c)\cdot q_{LR} + e\cdot\delta\cdot(w_o - w_z) \tag{3.17}$$

The collinearity effects between q_{LR} and $\delta\cdot(w_o - w_z)$ are usually small and this is likely to yield less unbiased parameter estimates than variant A.

3.3.3 Multistep Regression Approach

As shown in the next section, even the two-step regression approach yields biased parameter estimates and a more sophisticated estimation procedure, termed the multistep regression approach, has been found to give acceptable identification. Multistep regression is different from standard stepwise forward regression (Draper and Smith, 1981) where regression parameters are introduced in the model according to statistical criteria, namely according to the extent to which a parameter explains the residual variation of the independent variable at each step. The stepping rule of the multistep procedure proposed here is based on physical attributes.

The multistep approach involves four steps, i.e., four regressions are performed as against only two in the two-step. The various steps involved in the multi-stage regression are shown in Table 3.1. For the type of regression, "2P", two-parameter indicates a simple linear regression model in scatter graphs, and "4P", four-parameter means a four parameter, change point model of scatter graphs (Ruch and Claridge, 1992). The "4P" model is often useful when describing thermal energy use in multi-zone, commercial buildings. The model is fit to data both to the left and right of the change point.

Previous work (for example, Pedersen and Mouen, 1973; Subbarao, 1988) seems to suggest that even very small model mis-specification errors and noise in the data, have the effect of introducing bias in the physical parameters estimated by multiple regression, and so estimating one parameter at a time seems best. Note also that this procedure does not allow coefficient 'a' in eq. (3.11) to be estimated and so T_z cannot be identified. This, however, is not a serious limitation since the range of variation of T_z is fairly narrow for most commercial buildings. How this identification scheme is superior to the other two schemes will be illustrated in the next chapter.

Table 3.1 Steps involved in the multistep regression approach

	Dependent Variable	Regressor Variables	Type of Regression	Regression Coeff. Identified (see eq. 3.11)
Step 1	$Q_{B,1\text{-}zone}/A$	q_{LR}	2P	b
Step 2	$Q_{B,1\text{-}zone}/A - b \cdot q_{LR}$	T_o	2P or 4P	d
Step 3	$Q_{B,1\text{-}zone}/A - b \cdot q_{LR} - d \cdot T_o$	$q_{LR} \cdot \delta$	2P	c
Step 4	$Q_{B,1\text{-}zone}/A - b \cdot q_{LR} - d \cdot T_o$	$(w_o - w_z) \cdot \delta$	2P or 4P	e

CHAPTER IV

EVALUATION OF DIFFERENT PARAMETER IDENTIFICATION SCHEMES

4.1 Introduction

The best way to evaluate the soundness of a particular parameter identification scheme is to perform "computer" experiments using synthetic data. It is widely used in engineering disciplines, and also in a few building energy studies (Meier et al., 1988). The advantage of using such pseudo-data is that the "correct" model coefficients of the regressor variables are known exactly, thereby providing a basis for meaningful evaluation. Another advantage of using such synthetic data is that "noise" can be eliminated. In other words, the effects of numerous and unaccounted secondary physical influences can be removed from the model and a clean or "idealized" data set can be achieved on which various estimation methods could be evaluated. Using synthetic data can thus be likened to performing controlled experiments on a piece of equipment in a laboratory before installing it in the field. If the estimation process does not work satisfactorily with such "idealized" data, it is very unlikely that it will work with actual data. Thus a necessary but not sufficient condition is that the parameter estimation process should work satisfactorily with synthetic data before applying it to actual data.

There are two ways of performing such "computer" evaluations: one is to use a stochastic approach such as the Monte Carlo method (see for example, Pindyck and Rubinfeld, 1981), and the second is to use a detailed and adequately validated building and HVAC system simulation computer program to generate the required energy use "data". In the physical sciences, the inclination is to use the latter approach since it provides additional insight into the model mis-specification issue, which the former method does not. So in this chapter, the latter approach is adopted.

4.2 Procedure and Description of Buildings

A commercially available detailed commercial building simulation computer program (Carrier, 1995) has been selected which allows hour by hour generation of the HVAC coil loads, i.e., both heating and cooling thermal loads. This microcomputer program requires that a location be selected, that the building geometry and materials be specified along with zone specification and orientation, that the lighting, equipment and people schedules be specified along with the specification of different day-types, the type of HVAC system and mode of operation. The program then simulates the building and HVAC system performance at three different levels: building loads level, system coil loads level and plant level (for which case primary fuel types and costs need to be specified). The simulated system coil loads (E_C and E_H) have been used and $Q_{B,1\text{-zone}}$ was deduced for the purpose of validating our macro model

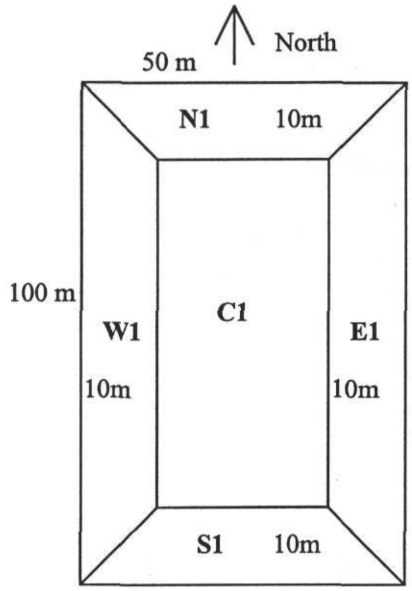

Figure 4.1 Floor plan of building B1 along with the zone designation

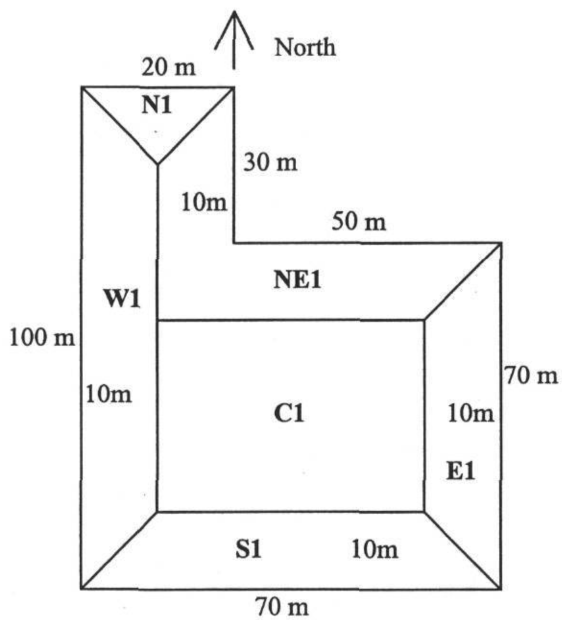

Figure 4.2 Floor plan of building B2 along with the zone designation

specification and parameter identification scheme.

Two building geometries (B1 and B2) were chosen as shown in Figure 4.1 and 4.2 Both have two floors, B1 having 10 zones (5 zones per floor with four zones facing the four major directions and one central zone) and B2 having 12 zones (6 zones per floor with the zone numbering shown in Figure 4.2).

Table 4.1 presents realistic range of variation of overall building and ventilation parameters along with a set of typical values used for simulations. Tables 4.2 and 4.3 provide additional details of the various zones of the two buildings. An occupancy density of 20 m^2/occupant has been chosen for each zone of both buildings and multiple realistic diurnal schedules for occupancy, lighting and equipment (different day-types for weekdays, weekends, holidays,...) were selected.

Two different climatic locations have been selected, namely Dallas, TX (a relatively hot and humid location) and Minneapolis, MN (a cold and dry location) in order to evaluate the various parameter identification schemes. The box and whisker plots (which indicate the mean, maximum and minimum, and the 25th, 50th and 75th percentiles of daily outdoor dry-bulb temperature and specific humidity difference for each of the four seasons as well as annual values, are shown in Figure 4.3 and 4.4 for

Dallas and Figure 4.5 and 4.6 Minneapolis respectively. Typical weather condition data were selected for both locations.

Table 4.1 Realistic range of variation of building parameters along with a set of typical values used for the simulations

Parameter	Units	Range of Variation	"Typical" Values
T_z	°C	21 - 24	22
RH_z	%	30 - 60	50
q_{LR}	W/m^2	10 - 40	20
k_s	-	1.05 - 1.20	1.20
k_l	-	0.1 - 0.4	0.167
m_v	$kg/s\text{-}m^2$	$0.3 - 7 \times 10^{-3}$	0.6×10^{-3}
UA_s/A	$kW/°C\text{-}m^2$	$0.5 - 3 \times 10^{-3}$	1.6 and 2.55×10^{-3}

Table 4.2 Geometry and occupancy details of the various zones of the two floor Building #1 (B1)

Zones	Floor area	Wall area	Window area	Roof area	No. of occupants *
-	m^2	m^2	m^2	m^2	-
N1	400	250	50	0	20
N2	400	250	50	400	20
E1	900	500	100	0	45
E2	900	500	100	900	45
S1	400	250	50	0	20
S2	400	250	50	400	20
W1	900	500	100	0	45
W2	900	500	100	900	45
C1	2400	0	0	0	120
C2	2400	0	0	2400	120
Total	10000	3000	600	5000	500

* 20 m^2 / occupant

Table 4.3 Geometry and occupancy details of the various zones of the two floor Building #2 (B2)

Zones	Floor area	Wall area	Window area	Roof area	No. of occupants *
-	m^2	m^2	m^2	m^2	-
N1	100	200	30	0	5
N2	100	200	30	100	5
NE1	800	800	120	0	40
NE2	800	800	120	800	40
E1	600	700	105	0	30
E2	600	700	105	600	30
S1	600	700	105	0	30
S2	600	700	105	600	30
W1	900	1000	150	0	45
W2	900	1000	150	900	45
C1	2500	0	0	0	125
C2	2500	0	0	2500	125
Total	11000	6800	1020	5500	550

* 20 m^2 / occupant

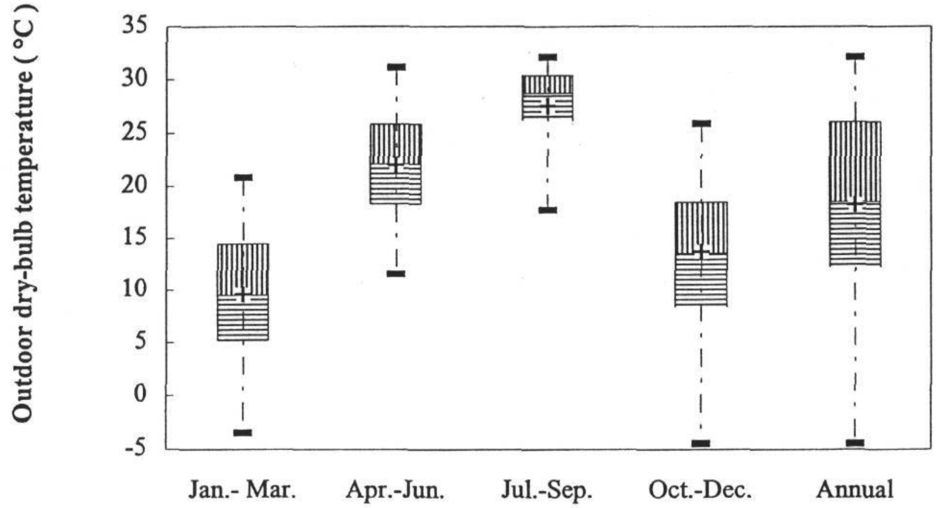

Figure 4.3 Seasonal and annual box and whisker plot of daily outdoor dry-bulb temperature for Dallas, TX

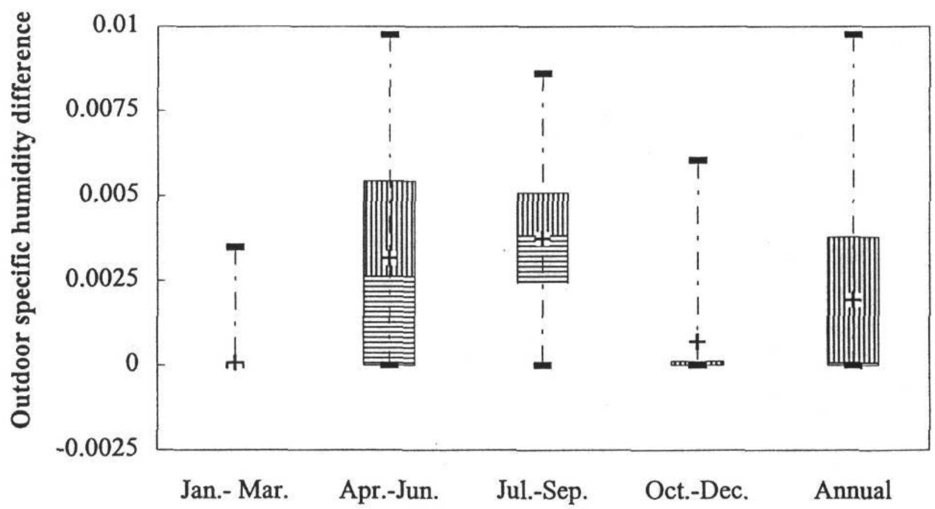

Figure 4.4 Seasonal and annual box and whisker plot of daily specific humidity differential for Dallas, TX

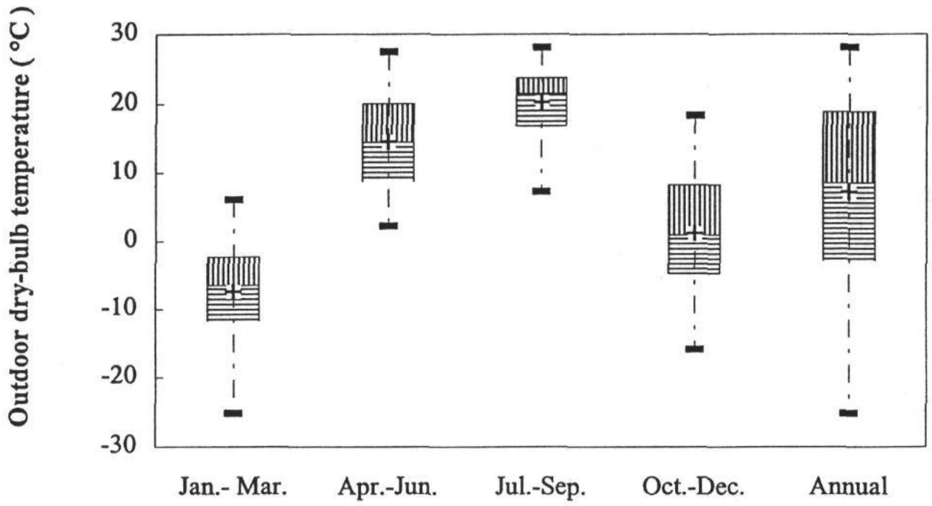

Figure 4.5 Seasonal and annual box and whisker plot of daily outdoor dry-bulb temperature for Minneapolis, MN

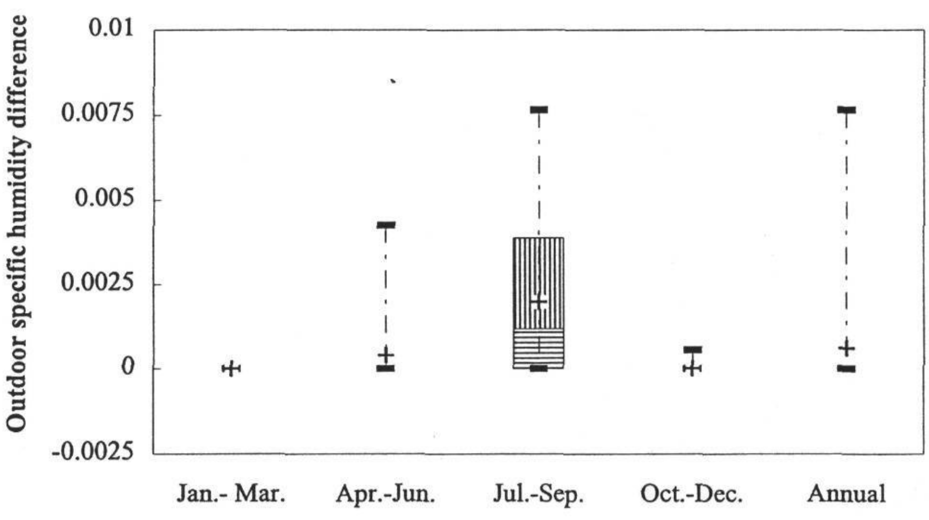

Figure 4.6 Seasonal and annual box and whisker plot of daily specific humidity differential for Minneapolis, MN

4.3 Using Daily Data for One Year

The HVAC simulation program has been run several times with various different scenarios. The effect of varying the number of day-types on the various identification schemes has also been investigated, specifically using 3, 5, 7 and 9 day-types during the year. It is found that more than 3 day-types are necessary to obtain meaningful regression results, and that having more day-types does little to improve the parameter identification accuracy any further.

Further, the effect of the mass of the various elements (walls and roof) on accuracy of the identification scheme has also been investigated using building B2 in Dallas assuming light, medium and heavy (20, 60 and 140 lb./ft^2) building materials. It is found that the identification accuracy is not affected by the choice of the building material type, and so subsequently our investigations have been limited to using the medium mass building material option. Note that the parameter identification is done on a daily scale, though the HVAC simulation is performed hourly.

How accurately the various parameter identification schemes (one-step, two-step variant A, two-step variant B, and the multistep procedures) are able to identify the "true" parameters is shown in Figure 4.7. It may be noted that simulation runs R1 to R5 contain the influence of solar radiation on building loads, while the effect of this

	R1	R2	R3	R4	R5	R6	R7	R8	R9
Identif. Scheme	1-step	2-A	2-B	Multi.	Multi.	Multi.	Multi.	Multi.	Multi.
Location	Dallas	Dallas	Dallas	Dallas	Dallas	Dallas	Minneap.	Dallas	Minneap.
Building	B1	B1	B1	B1	B1	B1	B1	B2	B2
Solar (?)	Yes	Yes	Yes	Yes	Yes	No	No	No	No
HVAC type	CV	CV	CV	CV	VAV	CV	CV	CV	CV

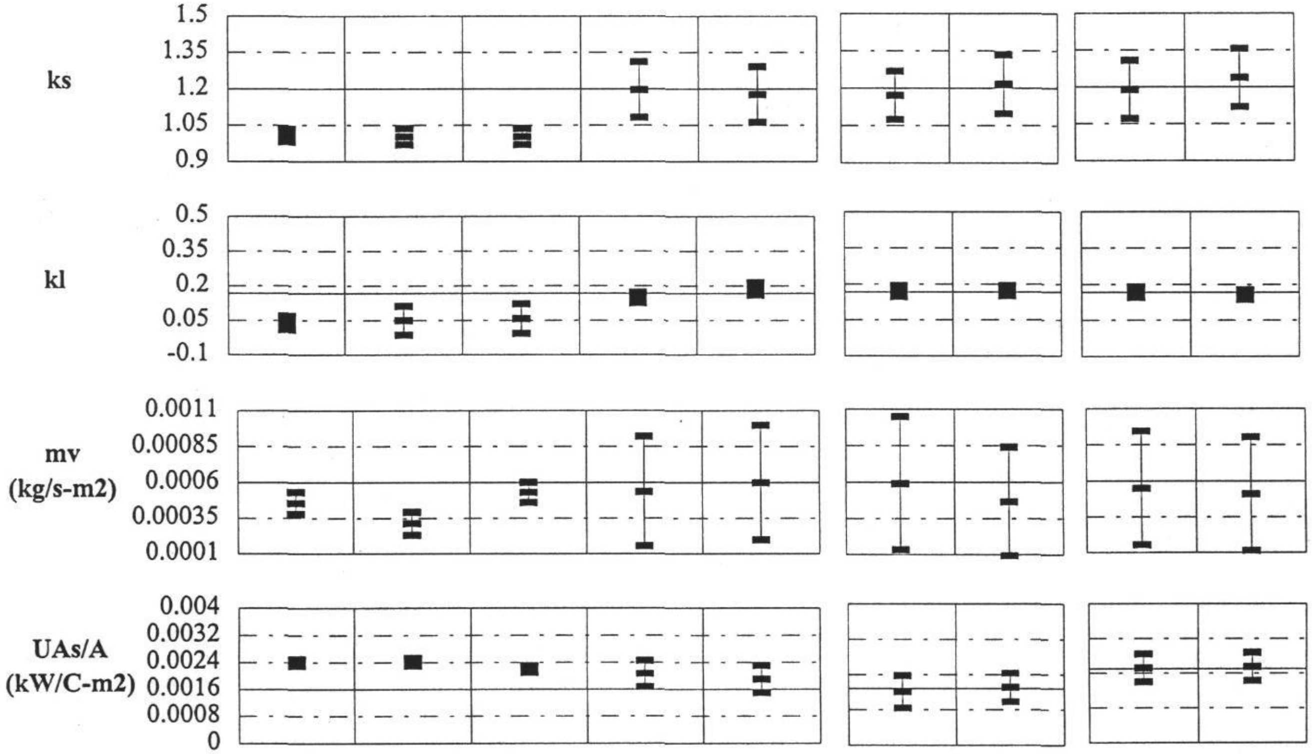

Figure 4.7 Summary of the various parameter identification schemes and simulation runs

variable has been "disabled" in the remaining four runs. The "true" values of each of the four parameters are indicated by a solid line, while the estimated parameters along with their standard errors deduced from eq. (3.14) are shown as small boxes. It is obvious that parameter identification is very poor for one-step and two-step procedures (R1, R2 and R3) (errors are more than 20%). The results that k_s is close to 1 and k_l is close to 0 can't reveal these two parameters' physical meaning at all. While, except for (UA_S/A), the other three parameters are very accurately (errors are less than 10%) identified by the multistep procedure (R4). The single step regression (using eq. 3.11) to daily $Q_{B,1\text{-zone}}$ values for buildings B1 and B2 in Dallas and Minneapolis gave excellent goodness of fit which is described in Appendix A (R^2 in the range of 0.97-0.99). So the goodness-of-fit by itself seems a necessary but not a sufficient condition to assure accurate parameter identification.

The identification scheme is still very accurate even when a VAV system is present as shown by case R4 in Figure 4.7. Note that the case of a constant outdoor air ventilation flow rate has been simulated rather than a constant outdoor fraction.

The remaining runs (R6 to R9) do not include solar effects and in such cases the multistep parameter identification scheme is accurate for both climatic types (Dallas and Minneapolis) and building geometries (B1 and B2). From Figure 4.7, it is noted that though there is no bias in estimating the parameter m_v, there is larger uncertainty associated with this parameter than with the other four parameters. Finally, it may be noted that the bias in identifying (UA_S/A) using the multistep approach when solar is present, is not really an error; it simply means that the overall steady-state heat loss coefficient has to be "modified" in order to implicitly account for solar effects (as is the case when the model shown in eq. 3.10 was formulated). This interpretation is consistent with the approach used by Vadon et al.(1991) and Knebel (1983).

A physical explanation as to why the multistep identification scheme is superior to the other schemes (specially the two-step scheme) is warranted. It is felt that the crux of the matter is the cross-correlation of the regressor variables. Table 4.4 presents the correlation coefficients of the various variables, as well as residuals Y1 and Y2 (see Table 3.1, $Y1 = Q_B - b \cdot q_{LR}$, and $Y2 = Q_B - b \cdot q_{LR} - d \cdot T_o$). It is noted that for both locations, q_{LR}, because of the finite number of schedules (5 day-types in this case) is the variable least correlated with $Q_{B,1\text{-zone}}$ as well as with the other regressor variables. Hence regressing $Q_{B,1\text{-zone}}$ with q_{LR} is <u>least</u> likely to result in the regression coefficient of q_{LR} (namely, b in eq. 3.11) picking up the influence of other regressor variables; i.e., the bias in the estimation of b is likely to be minimized. If a scheme of regressing $Q_{B,1\text{-zone}}$ with T_o first was adopted, the correlation between $Q_{B,1\text{-zone}}$ and T_o as well as between T_o and w_{oz} would result in coefficient d of eq. (3.11) being assigned more than its due share of importance, thereby leading to a bias in UA_S value (see R1, R2 and R3 in Figure 4.7) and thus underestimating k_s.

Table 4.4 Correlation coefficient matrix of various parameters for Dallas and Minneapolis at the daily time scale for Runs #6 and #7 (R6 and R7)

Dallas

	$Q_{B,1\text{-zone}}$	Y1	Y2	q_{LR}	T_o	W_{oz}	$q_{LR}\cdot\delta$
$Q_{B,1\text{-zone}}$		0.85	0.52	0.53	0.88	0.72	0.82
Y1	0.88		0.78	0.00	0.97	0.80	0.70
Y2	-0.86	-0.82		-0.27	0.59	0.68	0.44
q_{LR}	0.48	0.01	-0.30		0.11	0.07	0.42
T_o	0.91	0.97	-0.93	0.13		0.75	0.72
W_{oz}	0.57	0.59	-0.40	0.10	0.54		0.66
$q_{LR}\cdot\delta$	0.66	0.60	-0.48	0.27	0.58	0.72	

Minneapolis

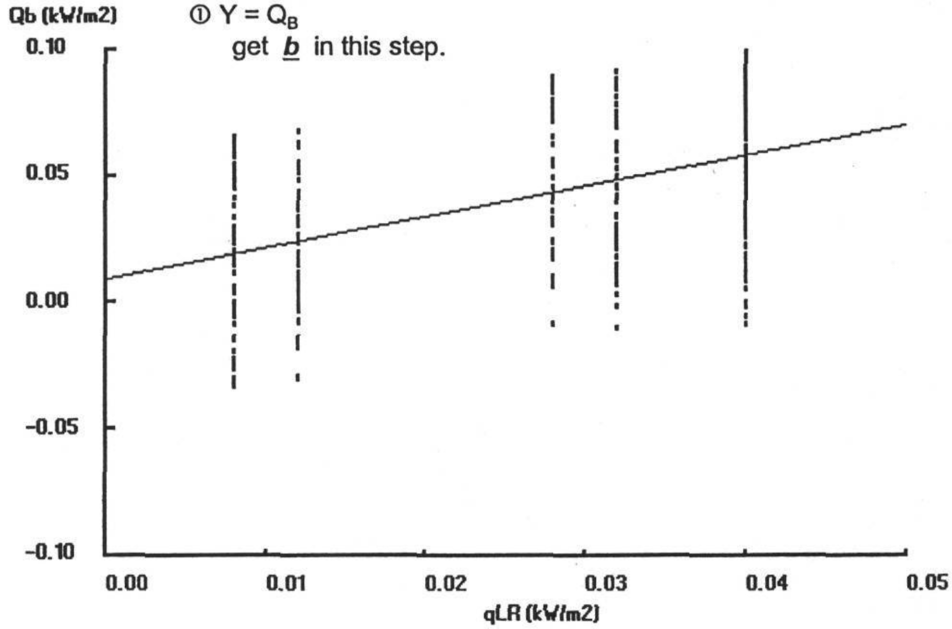

Figure 4.8 Step 1 of multistep regression method

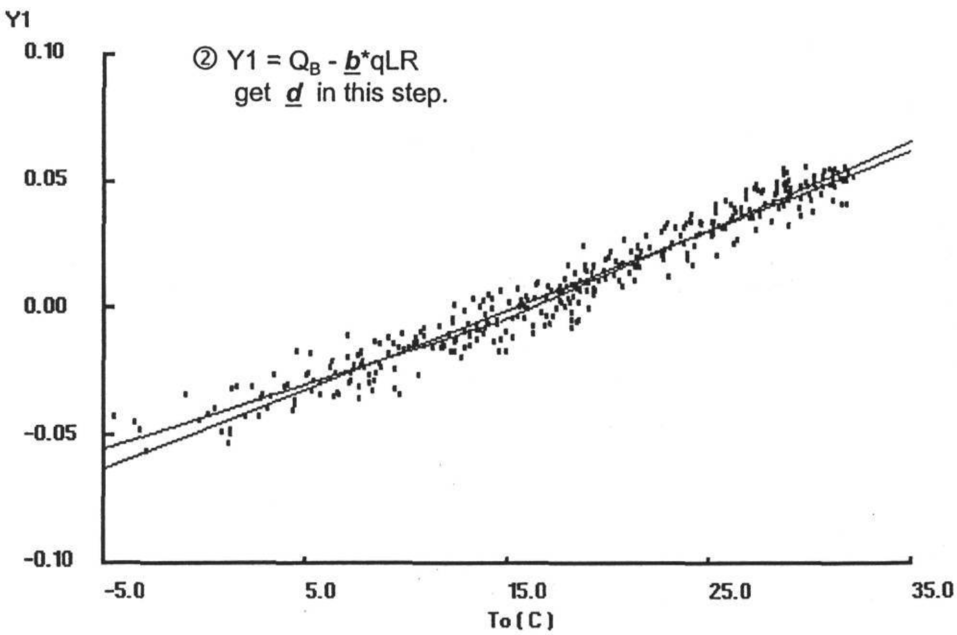

Figure 4.9 Step 2 of multistep regression method

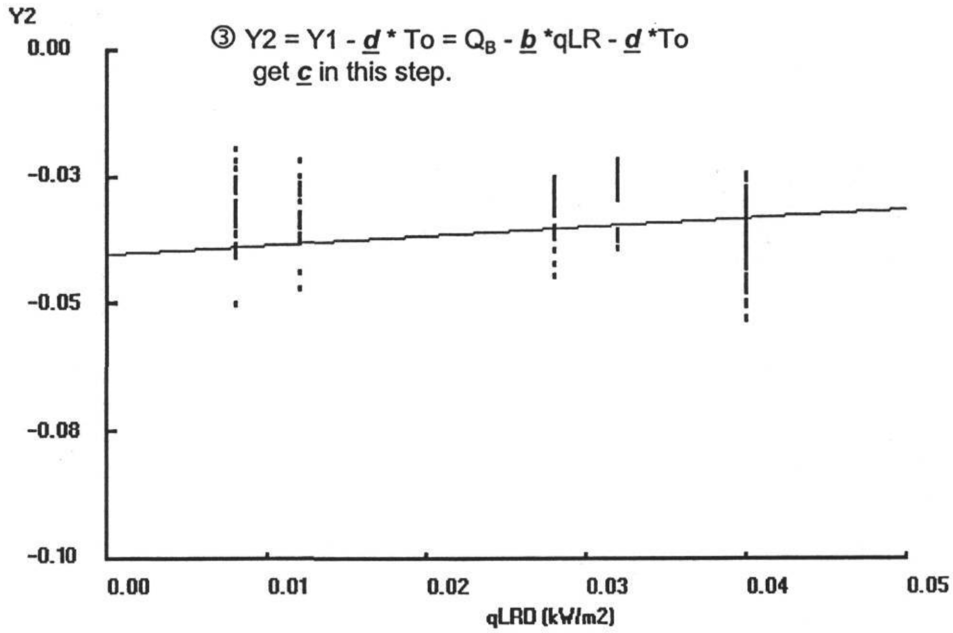

Figure 4.10 Step 3 of multistep regression method

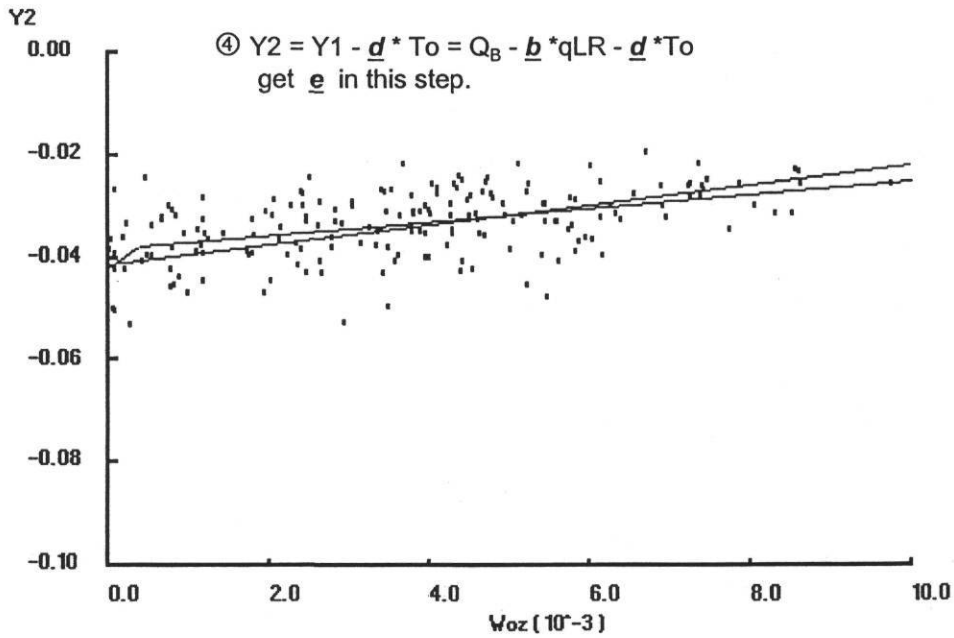

Figure 4.11 Step 4 of multistep regression method

The regression of $Q_{B,1\text{-zone}}$ versus q_{LR} for R6 is shown in Figure 4.8. The second step involves regressing the residual Y1 versus T_o because of the very strong correlation between both variables (correlation coefficients of about 0.97 - 0.99, see Table 4.4). As explained in an earlier paper (Reddy et al., 1994), one may use a four-parameter (4P) segmented linear model (as shown in Figure 4.9) in order to isolate the sensible and latent effects. Selecting the lower slope of the segmented model would yield a more accurate representation of the UA_S value because latent effects are usually not important in the lower temperature range. It is suggested that a simple linear model be used only if the slopes of the two segments are very close, a phenomenon observed when applying the multistep identification scheme to Minneapolis, which has relatively small latent loads even in summer.

It is found that equally good results are obtained by using step 3 and step 4 (see Table 3.1) in either order. Step 3 (see Figure 4.10) allows identification of the regression coefficient c in eq. (3.11), representing the building internal latent load, while step 4 (i.e. coefficient e of eq. 3.11, see Figure 4.11) identifies the corresponding regression coefficient associated with outdoor humidity.

4.4 Using Monthly Data for One Year and Daily Data during Different Seasons

The previous section dealt with evaluating the multistep identification scheme using a year-long daily data set. Since such a long data set is often not available in actual practice, we have also studied the identification accuracy of the multistep procedure under more realistic "field" conditions, as specified below:

(a) only monthly data over a year are available. This corresponds to utility bills being available.

(b) monitored data at daily time scales are available over a season only (i.e., three months).

The results of the identification scheme are summarized in Table 4.5 for Run 6, i.e. for Dallas climatic data, building B1, with no solar and using constant volume HVAC operation. It is noted that for (a), k_s and $(UA_S + m_v)$ can be identified very accurately. Though the parameters k_l and m_v are less accurately identified, the identification process using twelve utility bills is much more accurate than using seasonal daily data. With seasonal data, intuitively, one would expect identification for case (b) above to be more accurate when the range of variation of T_o and $[\delta \cdot (w_o - w_z)]$ during the particular season is large and covers a major portion of the annual range of variation of

Table 4.5 Results of multistep parameter identification using Dallas daily data of Run #6 when (i) monthly data only are available, and (ii) using daily data during different seasons of the year

	"True Values"	Using daily data during whole year	Using only 12 monthly data points	Using daily data during different seasons			
				J-M	A-J	J-S	O-D
k_s	1.20	1.17	1.19	0.94	1.17	1.12	1.38
k_l	0.167	0.17	0.051	0.121	-0.022	-0.114	0.075
$(UA_S/A + m_v)(\times 10^{-3})$	2.2	2.1	2.2	2.1	2.9	2.6	1.7
m_v $(\times 10^{-3})$	0.60	0.59	0.73	1.46	0.49	0.52	0.43

<u>both</u> parameters. Looking at Figure 4.3, 4.4, 4.5 and 4.6, it is noted that for both locations, the seasons Apr.-Jun. and Jul.-Sept. have the most variation in both parameters. A close look at Table 4.5 (applicable to Dallas), reveals that Apr.-Jun., the season with more variability, has the best overall identification, thus supporting our intuition.

A secondary speculation would be that a physical parameter would be most accurately identified depending on the extent to which that parameter varies during a season. For example, for Dallas (see Figure 4.3 and 4.4), the parameter associated with T_o (i.e., $UA_S/A + m_v$) should be most accurately identified during Oct.-Dec. (the season with the most variation in T_o). However, it is noted from Table 4.5 that this is not so. A similar conclusion is reached with the parameter associated with $[\delta \cdot (w_o - w_z)]$ (i.e., m_v). It should have been expected to be most accurately determined for Apr.-Jun., while from Table 4.5, it is noted that it is not so. On the whole, it can be concluded that parameter identification using seasonal data needs to be investigated further.

CHAPTER V

APPLICATION TO MONITORED DATA

5.1 Introduction and Objectives

In this chapter, monitored building energy use data will be used to perform a more careful evaluation of the proposed parameter estimation scheme and to apply the minimum heating and cooling energy use and EDE concept to an actual building HVAC system. In the last chapter, different estimation methods were evaluated using data obtained from a detailed building simulation computer code, and we have determined which estimation method is likely to minimize the confounding effect due to collinearity between the regressor variables and yield best estimates. We shall now apply the estimation methodology to year-long heating and cooling data from two institutional buildings in central Texas. Selected buildings from the Texas LoanSTAR program will provide the necessary high level of measured hourly building energy use data and weather conditions.

The ability to accurately determine building physical parameters from monitored building energy use data would allow the ideal building loads to be deduced. For the one-zone ideal building, eq. (3.2) can be used, while the equations of heating and cooling energy use for the two-zone ideal building are given by Reddy et al. (1997). We point out that the parameter (A_{int}/A) has little influence on the heating and cooling energy use of a two-zone building and so an approximate value based on geometry of the specific building could be used; subsequently the building energy use efficiency indices like the EDE and MEI can be determined for the selected buildings. These will provide certain insights into building HVAC system operation and their retrofit potential. In fact, this possible diagnostic evaluation of HVAC systems and their optimization is the basic and final purpose of the work on building physical parameter determination.

First, we shall present and discuss the differences in building loads and building energy use of CV and VAV systems from a theoretical framework, namely based on the results of the building HVAC system simulation program, HAP, used earlier. This comparison will be done to both EDE and MEI indices on a monthly basis. These comparisons will provide an initial indication of the energy use efficiency of CV and VAV systems and illustrate the energy conservation potential of VAV systems.

Subsequently the same kind comparison will be performed using data from two real buildings in the LoanSTAR program. One of the two buildings selected is the Business Building of the University of Texas at Arlington which had its HVAC system retrofit from a CV system to a VAV system in July, 1991. Thus pre-retrofit period data and post-retrofit period data of the same building can be used to compare building loads as well as EDE and MEI indices before and after the energy retrofit process. The other building, the Clinical Science Building of the University of Texas Medical Branch at Galveston had continuous commissioning (CC) work done in August, 1995, to optimize its CV system operation. So pre-CC data and post-CC period data can be analyzed in order to compare building loads as well as EDE and MEI indices to show the effect and benefit of this commissioning work. We know that the analysis of these two cases of actual building energy use data based on our suggested model and the proposed inverse method of estimating physical parameters will provide diagnostic insights into how to reduce the energy use in buildings.

As will be shown below, there are benefits in looking at both EDE and MEI indices in order to acquire a better understanding of the sources of energy inefficiencies in buildings. One of the objectives of this thesis is to illustrate, based on HVAC system simulations, the inherent inefficiencies in these different HVAC systems and how these can differently affect monthly energy use under different operating conditions. The insights gained from such a study could help (i) equipment manufacturers to develop different equipment and HVAC system designs and operation strategies, (ii) energy managers and building operators to gain diagnostic insights into how to reduce energy use at their buildings, and (iii) those involved in formulating state and federal building standards get a better appreciation of the energy trade-offs involved in using different HVAC system types pertinent to their specific requirements.

5.2 System Analysis with Synthetic Data

In chapter IV, energy use of a CV system and a VAV system has been simulated for a rectangular building (building #1) located in Dallas, TX in order to validate the multistep regression method. This synthetic energy use data from these two systems can also be used to generate the different energy use efficiency indices under CV and VAV system operation. Parameters estimated from the proposed multistep regression method can be used to determine the ideal two-zone building load. Finally the MEI and EDE indices can be estimated on a monthly basis. We have investigated how daily MEI and EDE indices compare with monthly indices. We found that due to the large number of data points and the spread due to day to day changes in outdoor humidity levels and due to changes in internal loads, scatter plots of these indices versus outdoor temperature results in data clouds which mask many of the effects we wish to study. Hence we suggest that it is best to study efficiency indices at monthly time scales.

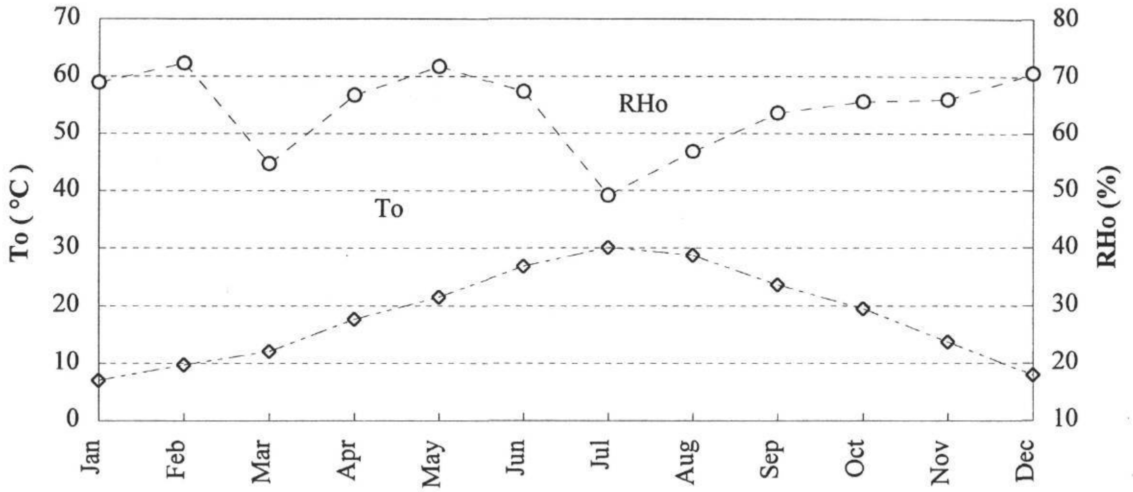

Figure 5.1 Monthly aggregations of the outdoor dry-bulb temperature and relative humidity data used to simulate the HVAC systems

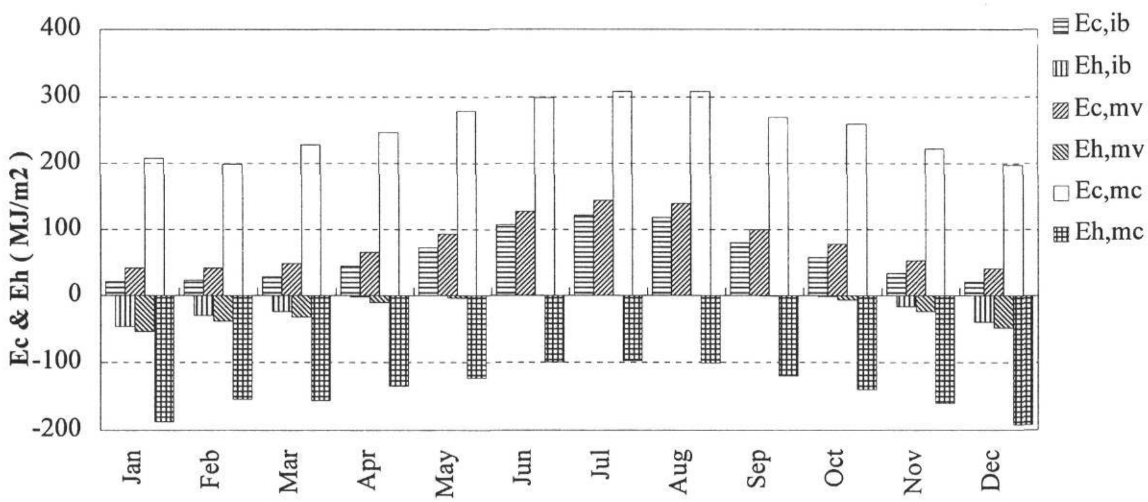

Figure 5.2 Sum of monthly energy use of the CV system, the VAV system and of the building load
Ec - Cooling energy use, Eh - Heating energy use
ib - Ideal building loads, mv - simulated VAV system
mc - simulated CV system

Figure 5.1 shows the monthly outdoor dry-bulb temperature and relative humidity under which these simulations were performed. Figure 5.2 presents the monthly sum of heating and cooling energy use for the above three situations, i.e. for a two-zone ideal building, the CV system and the VAV system. Since these three simulations are based on the same building under the same climatic conditions, a direct comparison could be undertaken here to illustrate differences between CV and VAV systems and the operation potential for VAV system. The energy uses, both for heating and cooling, of the CV system are clearly much higher than those of the VAV system due to the effect of simultaneous heating and cooling. The EDE and MEI indices discussed below allow clearer characterization of the energy efficiencies. Figure 5.3 presents the monthly EDE values for all three cases as a scatter plot against monthly mean outdoor dry-bulb temperature. Labels beside the points allow the reader to identify the point with the associated month of the year.

In Figure 5.3, EDE values scatter as expected, with EDE calculated from the two-zone building load being high most of the time, EDE for the VAV system being next and very close to the building EDE values calculated from building load, and EDE of the CV system being lowest. Note the drop in energy efficiency in the range of T_o values less than about 18 °C which corresponds to the months of January, February, March,

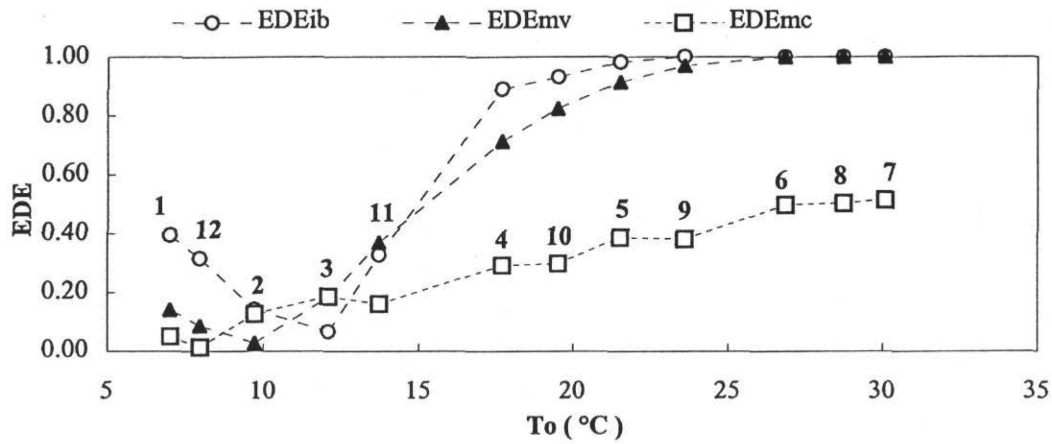

Figure 5.3 Monthly EDE for CV system, VAV system and building load

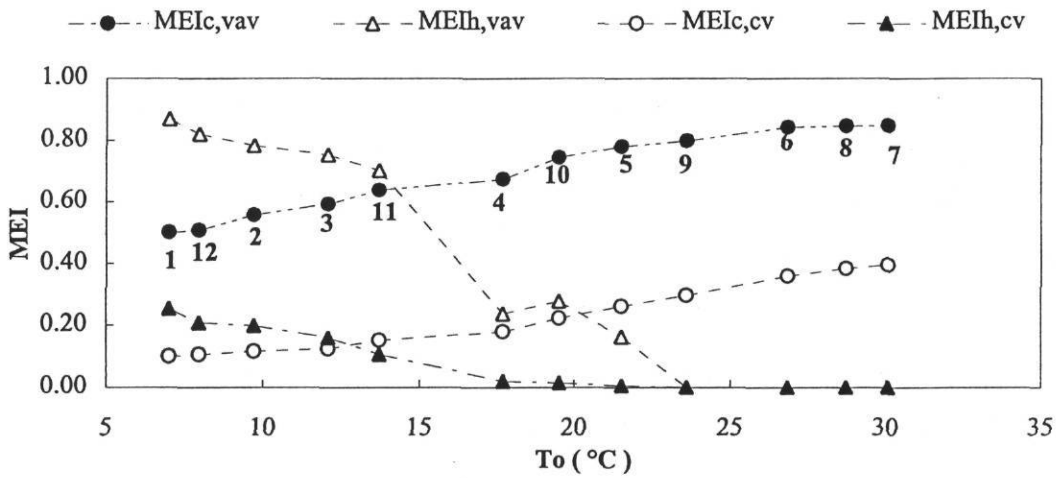

Figure 5.4 Monthly MEIc and MEIh for CV system, VAV system and building load

November and December. Though the energy use efficiency is low, the quantity of energy use is also low during these months (see Figure 5.3)

Though the EDE weights the absolute magnitudes of E_C and E_H and thus provides a single relative measure, it has some limitations as can be seen from Figure 5.3, when the outside air temperature is in the range of 10 °C to 15 °C. The ideal building EDE value is lower than those of the CV and VAV systems during March. This is because EDE is a ratio defined as $[(E_C-E_H)/(E_C+E_H)]$ and though both E_C and E_H for the building loads are lower than the HVAC system loads, the ratio turns out to be lower. EDE values in this temperature range are misleading. Note that for February, EDE of the CV system is higher than that of the VAV system. So the EDE can not properly reflect the energy use efficiency over a certain outdoor temperature transition period.

This drawback is overcome with the MEI indices. Figure 5.4 presents monthly MEI values for VAV and CV system operations of the #1 building. MEI values are also meaningful indices that reflect system operational energy use efficiency. For example, cooling MEI values for the VAV system when outside dry-bulb temperature is above 20 °C are around 0.80, which means that under these conditions, the VAV system consumes cooling energy (1/0.8)=1.25, i.e. 25% higher than that required for an ideal two-zone building. The corresponding cooling MEI values for the CV system are between 0.20 to 0.40, with cooling energy consumption being two and one-half to five times that of the building load. So the excess energy used by CV and VAV systems as compared to an ideal building, is quantified in terms of heating and cooling separately.

The MEI index by itself also has a limitation. When outside air temperature is high during summer, no heating is required for the ideal building and $E_H = 0$. In this situation, no matter what the value of E_H for the CV system or the VAV system, the monthly system MEI_H values calculated will be 0. In this period, MEI_H can't serve as a useful index for energy use efficiency. On the other hand, this is not a limitation for MEI_C values. Cooling energy is needed in commercial buildings are needed all year (especially in the interior zone) and so monthly MEI_C values do not go to zero.

From the monthly EDE and MEI plots discussed above, we realize why one should look at EDE and MEI indices together. Each index provides insights into HVAC efficiency at different outdoor dry-bulb temperature ranges which neither one alone can. EDE is an index calculated from both E_C and E_H jointly with attention to the hot and cold stream mixing phenomenon during HVAC operation, while MEI_C and MEI_H calculated from E_C and E_H separately provide insights into inefficiencies of each of the hot and cold streams individually.

In the following study, we shall look at how EDE and MEI indices vary for two monitored buildings under four operating modes. However, this requires that physical parameters be estimated first in order to calculate building loads which are required for determining EDE and MEI. Since the multistep regression method has been found to yield the most accurate estimation, will be used in the estimation process which will be performed for this study. This will also provide a means for assessing how well the estimation process works when applied to real energy use data.

5.3 Building Description

Two institutional buildings, one located at the University of Texas at Arlington, and the other at the University of Texas Medical Branch in Galveston, have been selected for analysis. The first building had air-side retrofits installed, namely the dual-duct constant air volume system has been converted to variable air volume operation. The other one had some continuous commissioning (CC) work performed, such as EMCS operational schedule optimization and hot air damper retrofit. Table 5.1 presents key characteristics of both buildings and their air handling systems. In the following study on physical parameter identification, one year of monitored data have been selected for analysis, namely November 1991 to October 1992 for the BUS building and the whole year of 1995 for the CSB building. The monitored data are from the LoanSTAR database where monitored data is stored after undergoing cleaning and consistency-checking.

Table 5.1 Key characteristics of buildings studied

Bldg.	Site	Use	Area (m^2)	HVAC system type	retrofit date	CC date	Comments
BUS	Arlington	classrooms, lecture halls	14,000	3 VAV dual duct AHUs	7/12/91-8/1/91	—	VAV retrofit
CSB	Galveston	classrooms, offices, labs	11,600	1 CV AHU	7/1/92-8/1/92	9/95	CV retrofit & CC

Table 5.2 Multistep regression results with monitored building energy use data

	BUS	CSB
Site	Arlington	Galveston
System	VAV	CV
Data Period	11/92 ~ 10/92	1/95 ~ 12/95
k_s	1.64	0.58
k_l	0.035	0.994
m_v (kg/s-m^2)	0.00019	0.00093
UA_s/A (kW/°C-m^2)	0.0019	0.0033

5.4 Parameter Identification

Physical parameters have been identified for the BUS and the CSB buildings using the multistep regression method. Table 5.2 presents the results obtained for these parameters, while Figure 5.5 presents the results along with their respective standard errors in graphical form.

For the BUS building, the k_s value is equal to 1.64, implying that on a year round basis the internal sensible load for this building is a little more than one and one-half times the load from lights and receptacles. Such a value is rather high and suggests that some portion of the internal loads are not being monitored (we could not verify this, however). k_l is a small value, close to zero (=0.035), meaning that this building has small internal latent loads. Fresh air intake is also on the low side, while the value of (UA_s/A) seems normal.

Compared with these values, the CSB building has a much smaller k_s value of 0.579, which is even less than 1. This can occur when monitored light and receptacle data also includes equipment located outside the air-conditioned space. It has a much larger k_l value, indicating that internal latent loads are larger, which is reasonable, given that it is a laboratory facility located in a coastal area. It also has a larger fresh air volume intake and a larger building envelope heat transmission coefficient, both of

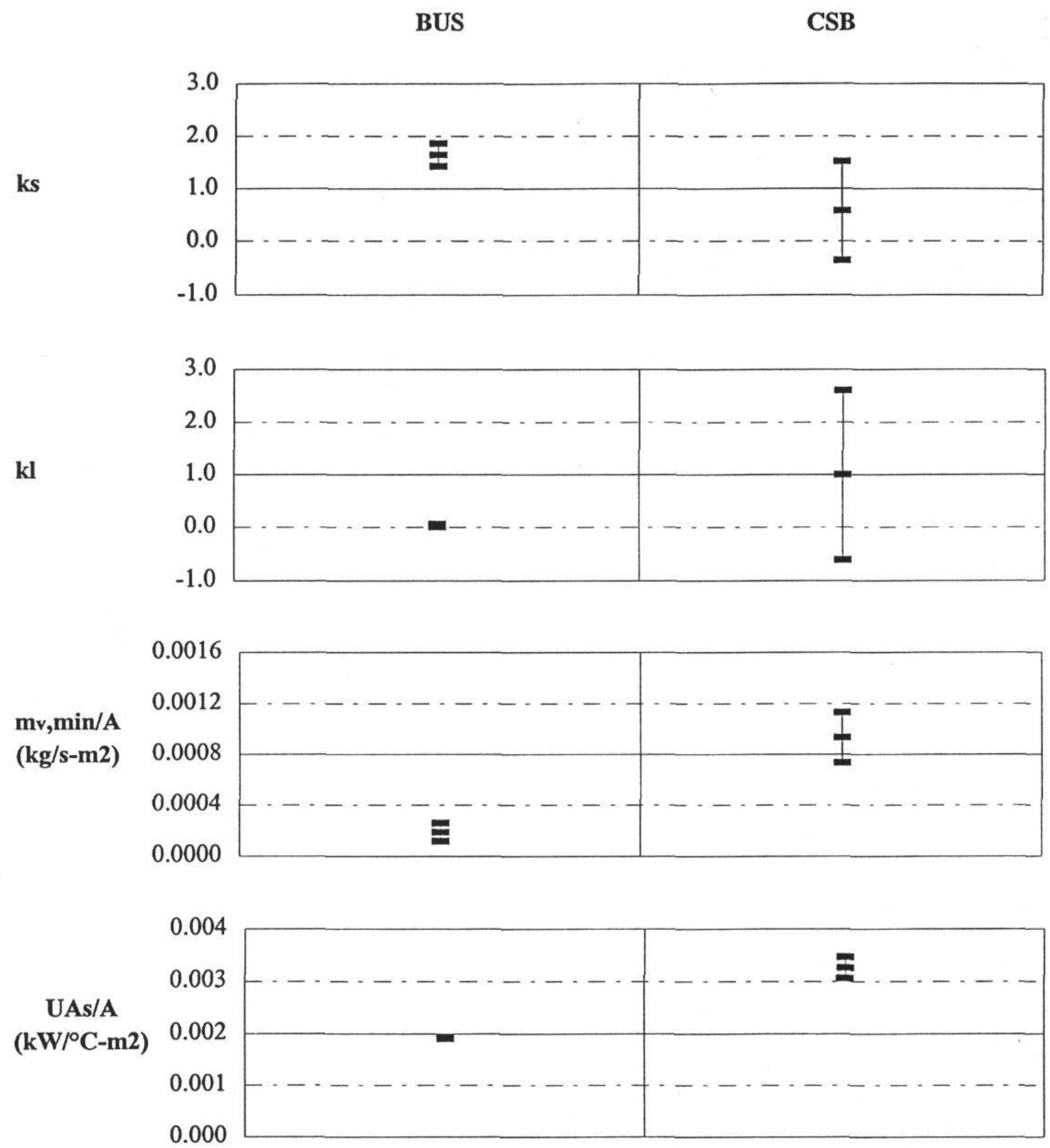

Figure 5.5 Multistep regression results with monitored building data

which mean that more energy needs to be consumed to maintain satisfactory indoor air conditions.

Based on the physical parameters determined for these two buildings, we shall analyze the building energy use as was done with the simulated energy use data in the previous section. For the BUS building, the effect of retrofit will be explored by comparing energy use and efficiency indices of pre-retrofit data and post-retrofit data. For the CSB building, the benefits of continuous commissioning (CC) work can be evaluated using pre-CC and post-CC data.

5.5 Effects of CV to VAV Retrofit on EDE and MEI

The Business Building at the University of Texas at Arlington had a HVAC system retrofit from a CV system to a VAV system in July, 1991. So, a comparison of energy use and other indices of a CV system and a VAV system can be done here to illustrate the effects on energy efficiency improvement brought about by the retrofit.

In this section we have calculated the ideal two-zone building loads from eq. (3.2) using physical parameters determined above, and then evaluated the corresponding EDE and MEI indices on a monthly basis. Climatic conditions are also averaged on a monthly basis for the corresponding location. This information provides a means of

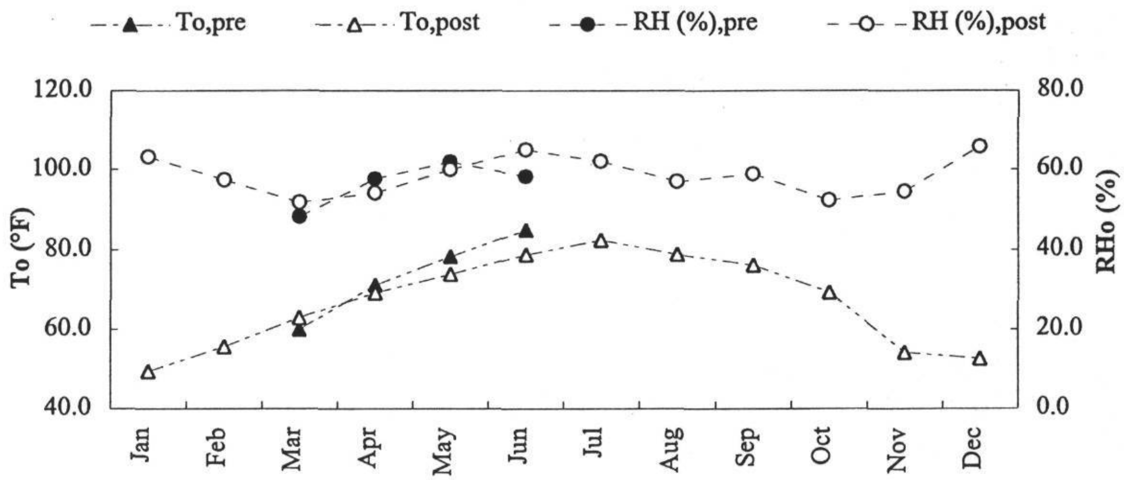

Figure 5.6 Monthly outdoor dry-bulb temperature and relative humidity conditions under which the HVAC systems were analyzed for the BUS building

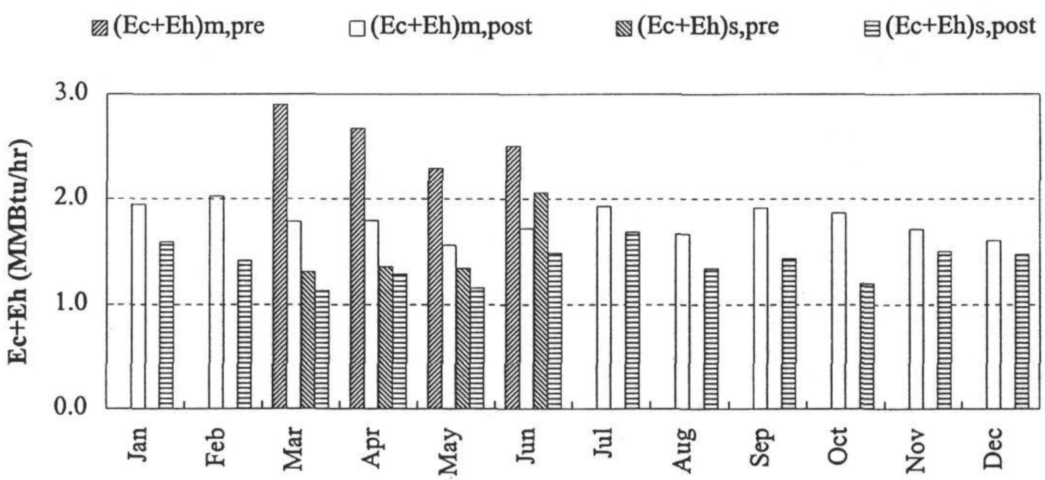

Figure 5.7 Monthly average of energy use for the BUS building pre and post retrofit

comparing pre-retrofit and post-retrofit building energy use as the system undergoes a retrofit from a CV system to VAV operation.

Figure 5.6 plots the monthly climatic conditions of the two selected monitored data periods, both of outside air temperature and relative humidity. We note that there is a little difference between the two periods.

Figure 5.7 presents the monthly average heating and cooling energy use of the ideal two-zone building and of the HVAC system for both periods. Monthly average building load changes a little because of changes in outdoor climatic condition from year to year. On the other hand, monthly average heating and cooling energy use have clearly decreased, almost by 30% after retrofit.

Figure 5.8 and Figure 5.9 show the month-by-month variation of the EDE and MEI indices as a scatter plot versus T_o. In Figure 5.6, we notice that all of the pre-retrofit outdoor air dry-bulb temperature values are in the range above 60 °F, and so the limitation of the EDE index (as pointed out in the previous section) during the transition period is not reflected here. EDE values for the VAV system are apparently higher than values for the CV system, indicating an improvement of energy use efficiency. The EDE plot can provide more insight than the above obvious observation. Consider April (i.e. month number 4) during the pre-retrofit period. The

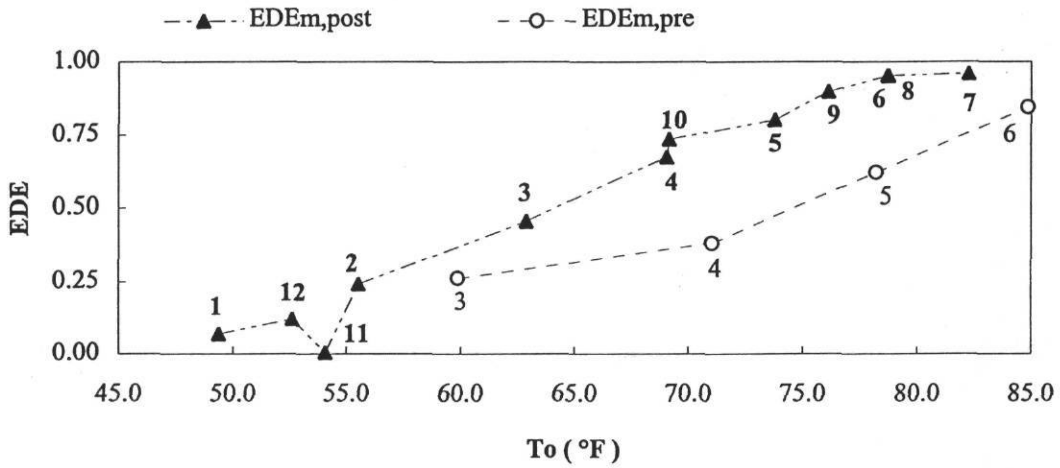

Figure 5.8 Monthly EDE for for the BUS building pre and post retrofit

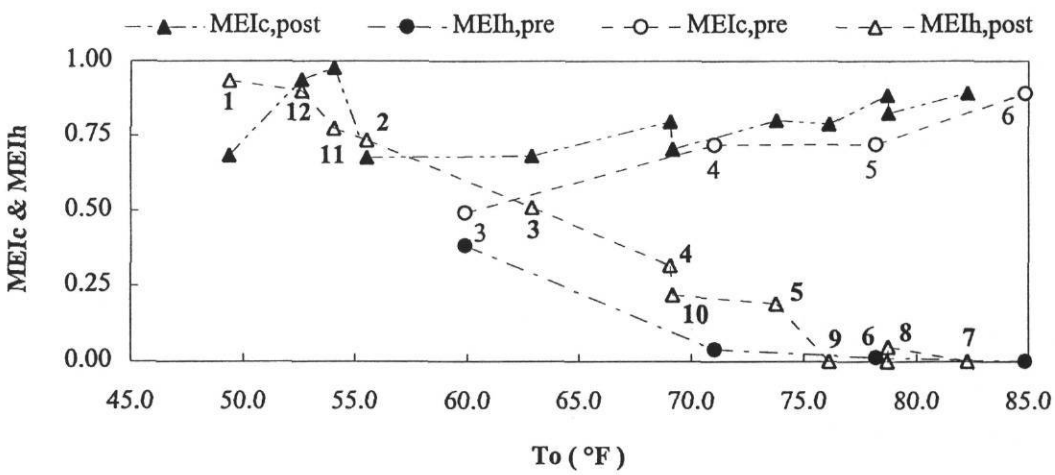

Figure 5.9 Monthly MEIc and MEIh for for the BUS building pre and post retrofit

EDE(CV) at 72 °F is only 0.375, while the EDE(VAV) at 72 °F is 0.75. Hence, in terms of total energy, the VAV system at this T_o value is twice as efficient as a CV system. Whether this improvement is due to savings in either the cooling energy use or the heating energy use can be determined from the MEI plots shown in Figure 5.9. It is concluded that since MEI_C is practically unchanged due to the retrofit, while MEI_H under VAV has improved substantially, the energy savings achieved are due to reduction in heating energy use.

Similarly, for VAV operation, conclusions can be drawn from the MEI plot: both MEI_C and MEI_H improve. The limitation of the MEI_H index during high outside air temperature values mentioned earlier can also be seen here. All the MEI_H values in that region are zero for both the CV system and the VAV system, thus providing little diagnostic ability.

Studying the EDE and MEI indices prior to and after the retrofit not only allows quantifying the extent to which the VAV system is more energy efficient than the CV system, but allows the quantification to be done on an absolute scale, i.e. based on ideal building loads. Since existing buildings are often operated under CV operation, retrofit from CV to VAV operation is highly desirable whenever possible.

At the same time, the VAV system energy use is still higher than the building load, indicating that there is potential to explore techniques to make the HVAC system more efficient, such as CC measures.

5.6 Effects of Continuous Commissioning on EDE and MEI

The Clinical Sciences Building of the University of Texas Medical Branch in Galveston had continuous commissioning (CC) work done to optimize its CV system operation in August, 1995. So data from pre-CC and post-CC periods will be compared to building load and the quantitative benefit of the EDE and the MEI indices to the CC work will be studied.

As previously, building loads are first calculated using physical parameters determined by the multistep parameter identification method and eq. (3.2). These building loads can be used to deduce the corresponding monthly EDE and MEI indices. Climatic conditions are also averaged for the site where the building is located. This information will allow a comparison of pre-CC and post-CC building energy use that will provide some insights about the effects of continuous commissioning work.

The month-by-month variation of outdoor air temperature and relative humidity of the two selected monitored data periods are shown in Figure 5.10. It is seen that relative

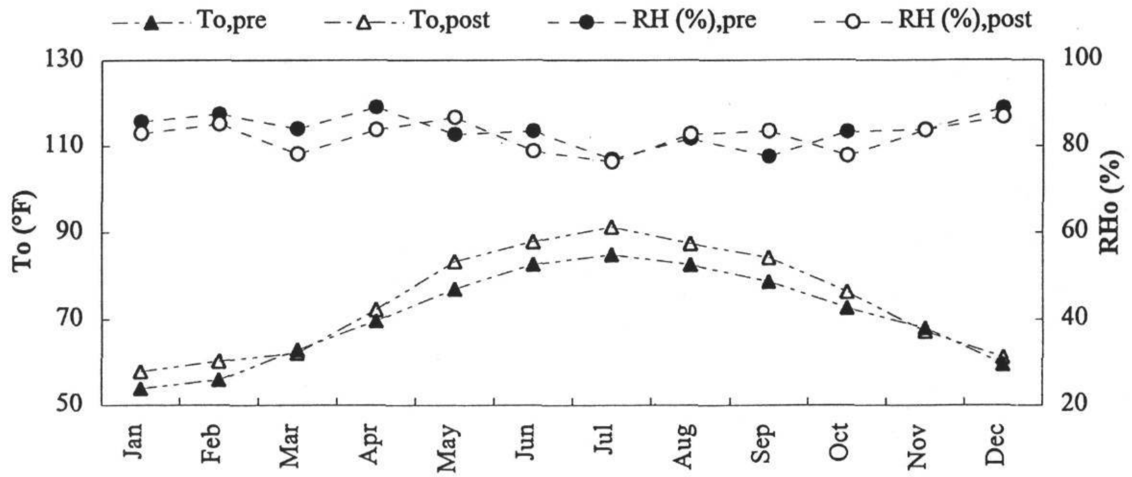

Figure 5.10 Monthly outdoor dry-bulb temperature and relative humidity conditions under which the HVAC systems were analyzed for the CSB building

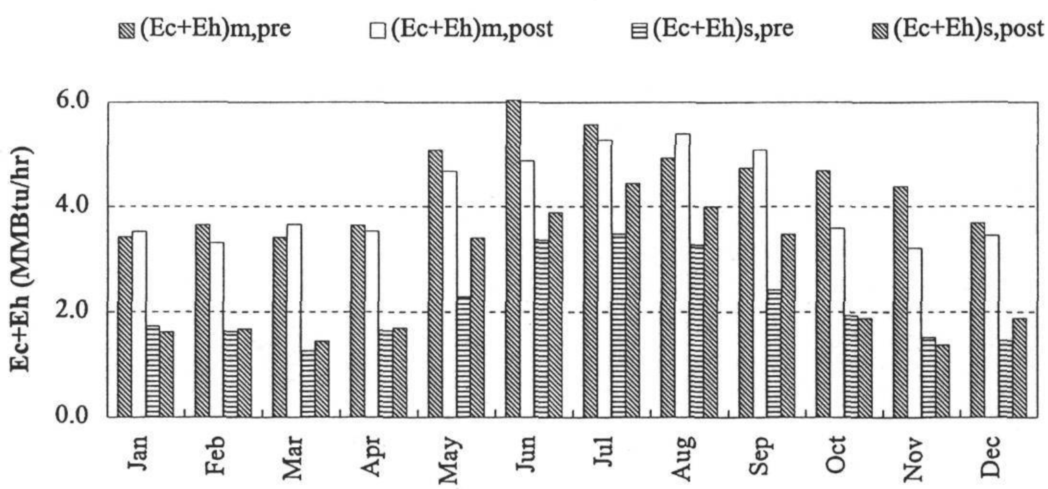

Figure 5.11 Monthly average of energy use for the CSB pre and post continuous commissioning

humidity values change a little but are fairly consistent during the two years, but outside air temperature is higher in 1996 than in 1994 for Galveston. This makes the building load higher in 1996 than in 1994, but this should not affect our comparison of pre-CC and post-CC energy use because our models account for this effect explicitly.

Figure 5.11 presents the monthly average heating and cooling energy use during both pre-CC and post-CC periods and their respective monthly average building loads. Because of changes in weather from pre-CC and post-CC periods, we note that post-CC use during, say March, is higher than the pre-CC use. This does not mean that EDE has decreased because the ideal building loads have increased. From January to April and October to December, the monthly average values of ideal building loads change little because the outdoor climatic condition change from pre-CC to post-CC is small. The monthly averages of heating and cooling energy use also do not change much. From May to July, however, we notice obvious savings in energy because monthly averages of ideal building load have increased during 1996 as compared to 1994 due to hot weather, whereas monthly averages of heating and cooling energy use have actually decreased. June is a model for this phenomenon, with ideal building load increasing, whereas system energy use drops greatly because of continuous commissioning work done there.

Figure 5.12 and Figure 5.13 show the month-by-month variation of EDE and MEI indices respectively. In Figure 5.10, we note that the pre-CC plots are not as distinctly different as was the case for the BUS building which had retrofits performed to it. This is because the energy savings due to CC in CSB are less than those in BUS. Also the day-to-day variations in a month are not properly characterized by its mean value, and so the EDE plots for pre-CC are not as distinct as in the previous building. However, an overall improvement in EDE for the post-CC period is obvious.

The MEI index seems to provide a clearer picture in this case as can be seen in Figure 5.13. This is partly because MEI evaluates E_C and E_H separately through the MEI_C and MEI_H indices. Both MEI_C and MEI_H improve somewhat with improvement in the MEI_C values being more pronounced. But the limitation of MEI_H in the high outside air temperature ranges is also noticeable. All the MEI_H values in that region are zero for both periods, and this index provides no diagnostic insight.

So from the comparison performed above, continuous commissioning work done to the HVAC system has been reflected by an increase in EDE and MEI which allows quantification in energy efficiency as discussed in the previous section. As mentioned in the preceding section, this kind of maintenance and operation optimization work is very meaningful when a CV system can not be retrofitted to a VAV system for some reason. Energy use efficiency could be further promoted with continuous

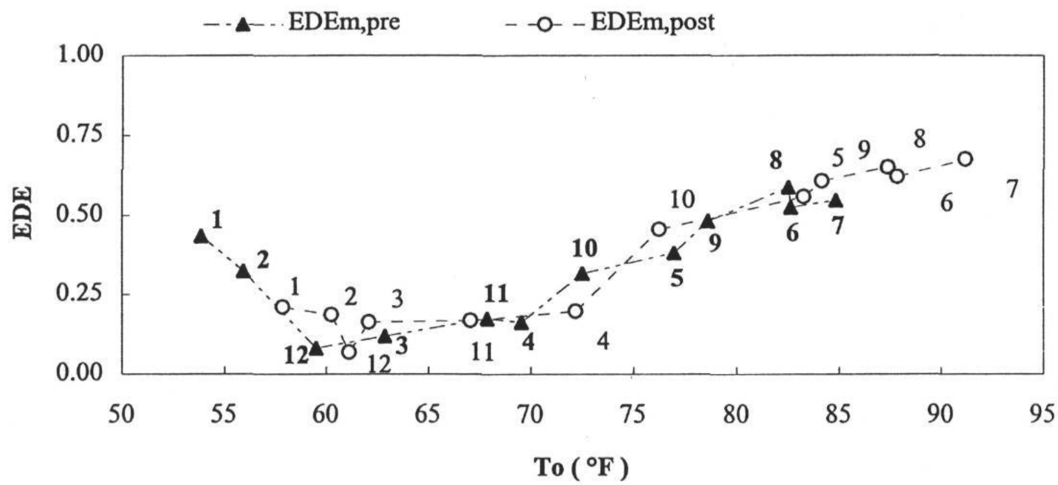

Figure 5.12 Monthly EDE for for the CSB building pre and post continuous commissioning

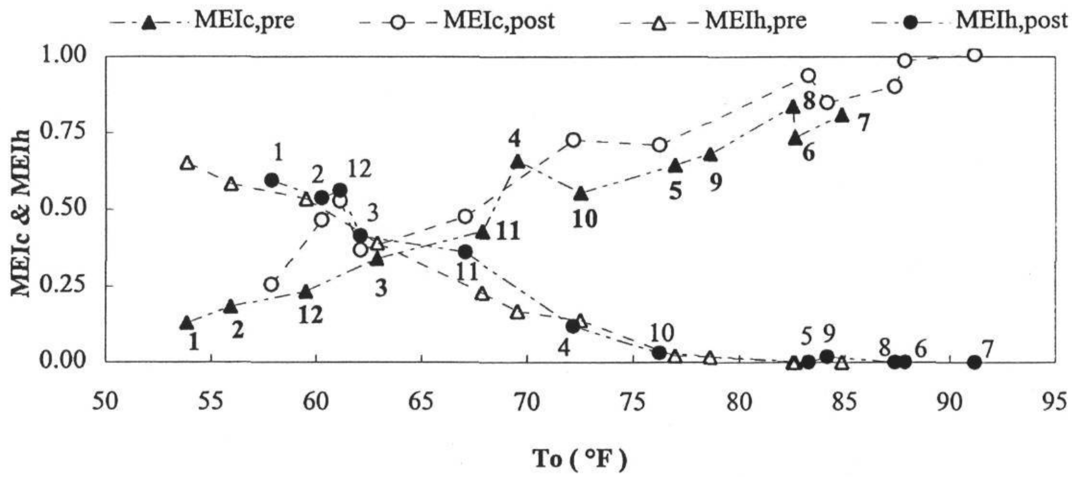

Figure 5.13 Monthly MEIc and MEIh for the CSB pre and post continuous commissioning

commissioning techniques. It is also practical to apply these techniques to VAV systems to make the operational efficiency even better especially when the energy use by the VAV system is still much higher than the building load.

5.7 Results and Conclusions

In this chapter, the parameter identification scheme and the insights provided by EDE and MEI indices have been discussed using monitored data from two institutional buildings located at different sites with different climatic conditions. Physical parameters identified seem to be physically consistent.

These physical parameter estimates have been used to calculate building loads for the buildings under different operating periods, allowing evaluation of the two building energy use indices. By means of building loads, building monitored energy use and EDE and MEI indices, the benefits of retrofit and continuous commissioning (CC) work have been clearly highlighted. For the BUS building, retrofit from CV to VAV operation improved EDE greatly for both heating and cooling energy use. For the CSB building, continuous commissioning work resulted in a dramatic reduction of cooling energy use, while heating energy use simultaneously decreased.

The advantages and limitations of EDE and MEI have been discussed, and conditions under which one index is better than the other have been pointed out. EDE captures energy use efficiency well except for the swing periods of the year. MEI is a better index during these periods, but is of little value when the outside air temperature is either too high or too low. Studying these two indices together can provide more insights into system operation and diagnostic ability of the HVAC system.

CHAPTER IV

SUMMARY

In this thesis, a simplified model appropriate for parameter identification is proposed and validated, and four different inverse parameter identification schemes are evaluated using heating and cooling data generated from a detailed building simulation program. Simulations were performed for two different building geometries and building mass levels using climatic data for Dallas, Texas and Minneapolis, Minnesota. This synthetic data was used to identify the best parameter identification scheme and to validate the model used, i.e., the one that is likely to minimize the confounding effect of collinearity between the regressor variables, and yield the most accurate parameter estimates.

A multistep identification scheme has been found to yield very accurate results, and a more careful evaluation was performed to test its accuracy and stability (using synthetic data) against the effects of solar energy, HVAC system operation, internal load schedule, building thermal mass and geometry, and climatic location. The results came out to be very accurate under these conditions (errors are less than 10%). This method was also evaluated using data for different time periods.

Then it is applied to energy use data from two buildings monitored under the Texas LoanSTAR Program. These buildings are in different cities and have different HVAC systems. With physical parameters determined from the multistep identification scheme, two energy use indices, EDE and MEI, can be calculated. How they provide insights into the benefits brought by retrofit from a CV to a VAV system and by continuous commissioning work done to these two buildings respectively has been discussed. It is clearly demonstrated that a VAV system is much more energy efficient than a CV system, and that operational optimization techniques can be done to systems to greatly improve their energy efficiency. Functions and limitations of EDE and MEI are also discussed. The EDE index can not reflect energy use efficiency during the swing period of the year when monthly average T_o is around 55 °F to 60 °F , while the MEI_H index can not serve as a useful index during the high outside air temperature period when monthly average T_o is higher than 80 °F.

Based on these findings, it is suggested that the multistep regression approach can be used as an accurate and practical method for determining building physical parameters, and that the combined use of both EDE and MEI indices calculated from these parameters can provide insights about system and operational optimization potential of HVAC systems.

The multistep regression parameter identification process has been found to be very accurate when daily data over an entire year are used. Parameter identification accuracy using twelve monthly data points and daily data over three months of the year was also investigated, and certain criteria were identified regarding the climatic data which would provide a first indication of the seasonal identification accuracy. This issue needs to be investigated further in order to make the multistep regression method more applicable to analysis of measured commercial building energy use.

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APPENDIX A

COMPUTER EXPERIMENTS

A.1 Introduction

This appendix presents our preliminary effort to evaluate the three different parameter estimation methods discussed in chapter IV of the thesis by the Monte Carlo approach as mentioned, this involving generate synthetic energy use data from a specified mechanistic model, and by varying the amounts of random noise in the data, try to recover the initial parameter estimates. This technique should provide insights into which estimation method is likely to minimize the confounding effect of collinearity between the regressor variables, and yield the best parameter estimates. Results obtained in this way are very different from those obtained in chapter IV, and in fact may mislead the naive analyst. It is presented here to provide some background for future similar research work.

A.2 Application to Synthetic Data

The best way to evaluate a particular parameter identification scheme, is generally to perform "computer" experiments using synthetic data. This technique is widely used in engineering disciplines, and also in some building energy studies (for example, Meier et al., 1988). The advantage of using such pseudo-data is that the "correct" model coefficients of the regressor variables are known exactly, thereby providing a basis for meaningful evaluation. Another advantage of using such synthetic data is that "noise" can be eliminated. In other words, the effects of numerous and unaccounted secondary physical influences can be removed from the model and a clean or "idealized" data set can be achieved on which one can evaluate various estimation methods. If the estimation process does not work satisfactorily with such "idealized" data, it is unlikely to not work with actual data. Thus a necessary but not sufficient condition is that the parameter estimation process should work satisfactorily with synthetic data before applying it to actual data. Further, one has a systematic way of introducing progressively more noise in the model and studying its implication on the parameter identification process. Using synthetic data can thus be likened to performing controlled experiments on a piece of equipment in a laboratory before installing it in the field.

The following equation has been used for $Q_{B,1\text{-zone}}$ (deduced with solar effects set to zero) to generate year-long synthetic data using monitored daily values of q_{LR}, T_o and w_o for the WAG and BUS buildings:

$Q_{B,1\text{-zone}}$ = Mechanistic term + noise term i.e.

$$Q_{B,1-zone} = q_{LR} k_s (1+k_1\delta)A + (UA_s + m_{v,min} Ac)(T_0 - T_z) + m_{v,min} Ah_v \delta(w_0 - w_z)$$
$$+R.\overline{Q}_{B,1-zone}.k \qquad \text{(A.1)}$$

where the noise term contains three components:

(i) a normally distributed random number R with a mean value of 0 and standard deviation of 1,

(ii) the annual mean value of the building loads $\overline{Q}_{B,1-zone}$, and

(iii) k, a multiplicative coefficient that is a normalized measure of the introduced noise relative to the deterministic component of the model. Thus k=0.1 would imply that the data generated have a 10% noise level. k=0 would indicate a data set with no noise at all.

A.2.1 Building Description

Data from three institutional buildings, one located at the University of Texas in Austin, the other at University of Texas in Arlington and the third at University of Texas in Galveston, have been selected for analysis. Table A.1 presents key characteristics of all three buildings and their air handling systems. In this study, one year of post-retrofit data have been selected for analysis, namely December 1991 to

November 1992 for BUS building, August 1992 to July 1993 for WAG building and January 1993 to December 1993 for MLB building.

Table A.1 Key Characteristics of Buildings for Computer Experiments

Bldg.	Use	Area (m^2)	No. of floors	HVAC system type	Pre-retrofit dates	Post-retrofit dates
BUS (Arlington)	classrooms, lecture halls	14,000	A: 3 floors B: 6 floors	3 VAV dual-duct AHUs	3/91-6/91	8/91- current
WAG (Austin)	classrooms, offices, labs	5,350	5 floors	2 VAV dual duct AHUs	2/91-5/91	6/91- current
MLB (Galveston)	libraries, offices	6,250	6 floors	2 CV AHUs	6/91-7/92	8/92- current

A.2.2 Selected Parameter Estimation Approaches

As discussed in chapter 3, instead of dealing with heating and cooling energy use separately, it is more convenient to look at $Q_{B,1\text{-zone}}$ instead. The expression for $Q_{B,1\text{-zone}}$ is given by eq. (3.10). If solar effects are neglected, there are six physical parameters to be estimated: k_s, k_l, UA_S, m_v, T_z and w_z. In this appendix, these parameters will be estimated using three approaches already described in chapter 3 in detail.

Approach 1: One-step approach

This approach directly uses least-square multiple linear regression and is possible when monitored values of q_{LR}, T_o and w_o are available. For such a scheme, it is more appropriate to rewrite eq. (3.10), neglecting solar loads, as:

$$Q_{B,1\text{-zone}} = a + b \cdot q_{LR} + c \cdot \delta \cdot q_{LR} + d \cdot T_o + e \cdot \delta \cdot (w_o - w_z) \qquad \text{(A.2)}$$

From those five regression coefficients, parameters k_s, k_l, UA_S, m_v and T_z can be easily deduced.

Approach 2: Two-step approach

A key observation made from the year-long data set is that there are periods in the year (usually 2 months or so far the Texas locations selected) when $\delta \cdot (w_o - w_z) = 0$. This led to the suggestion that a two-step regression approach could be adopted as follows:

During the two-month period when $\delta\cdot(w_o - w_z) = 0$, eq. (A.2) reduces to

$$Q_{B,1\text{-zone}} = a + b\cdot q_{LR} + d\cdot T_o \qquad \text{(A.3)}$$

For the 10 months, eq. (A.2) remains the same.

There are now two ways of proceeding. One variant is to use eq. (A.2) as is, and determine coefficients a, (b+c), d and e from multiple regression. The previous values of a and d determined from eq. (A.3) are rejected and those determined from eq. (A.3) are retained and used to deduce the physical parameters. This approach is termed two-step <u>variant A</u>.

A second variant of the two-step approach, termed two-step <u>variant B</u>, retains the coefficients b and d determined from eq. (A.3) and uses the following modified equation to determine a, c and e:

$$Q_{B,1\text{-zone}} - d\cdot T_o = a + (b + c)\cdot q_{LR} + e\cdot\delta\cdot(w_o - w_z) \qquad \text{(A.4)}$$

In this variant, the data for regression are generated using $Q_{B,1\text{-zone}}$ minus $d\cdot T_o$, while d is determined from eq. (A.3) when doing the first step regression.

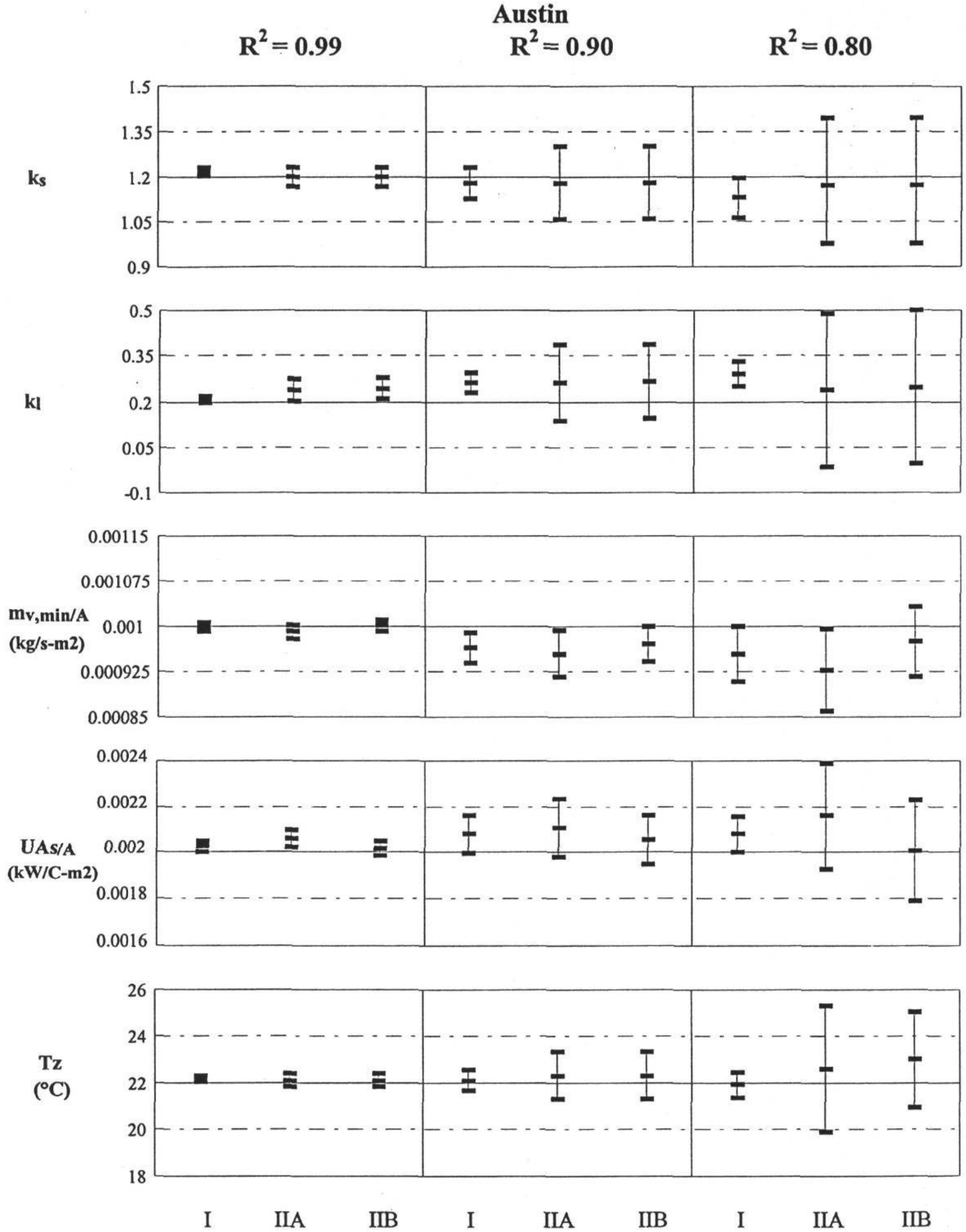

Figure A.1 Results of computer experiments with identification schemes of 1-step, 2-step variant A and B for different R^2 levels at Austin

A.2.2 Results Discussion

Results from the computer experiments are presented in Figure A.1 and Figure A.2. The accuracy of the various parameter identification schemes (one-step, two-step variant A, and two-step variant B) is shown for three values of R^2 and for the Austin building (see Figure A.1) and for $R^2 = 0.84$ at each of the three sites (see Figure A.2). The "true" values of each of the four parameters are indicated by a solid line, while the estimated parameters along with their standard errors deduced in chapter III are shown as small boxes. It is obvious that parameter identification is very accurate for one-step and two-step procedures at different R^2 levels in Figure A.1. The runs corresponding to $R^2 = 0.99$, means there is very little noise in the data set, and the regression results are very accurate with very small standard errors, as one would expect from statistics. For runs corresponding to R^2 equal to 0.90 and 0.80, progressively more error is introduced in identifying the parameters from regression, and the standard errors are larger. What is noteworthy is that these five parameters are very accurately identified by all three estimation procedure (one-step, two-step variant A, and two-step variant B). The errors are still within 10% when R^2 drops to 80%. Also, from Figure A.1, it seems that 1-step procedure is the best, because it has the smallest error and standard error. This results are contrary to those in chapter IV. The reason is that the Monte Carlo method does not give any insight into model mis-specification errors, which seems to be a more important source of parameter bias than the parameter

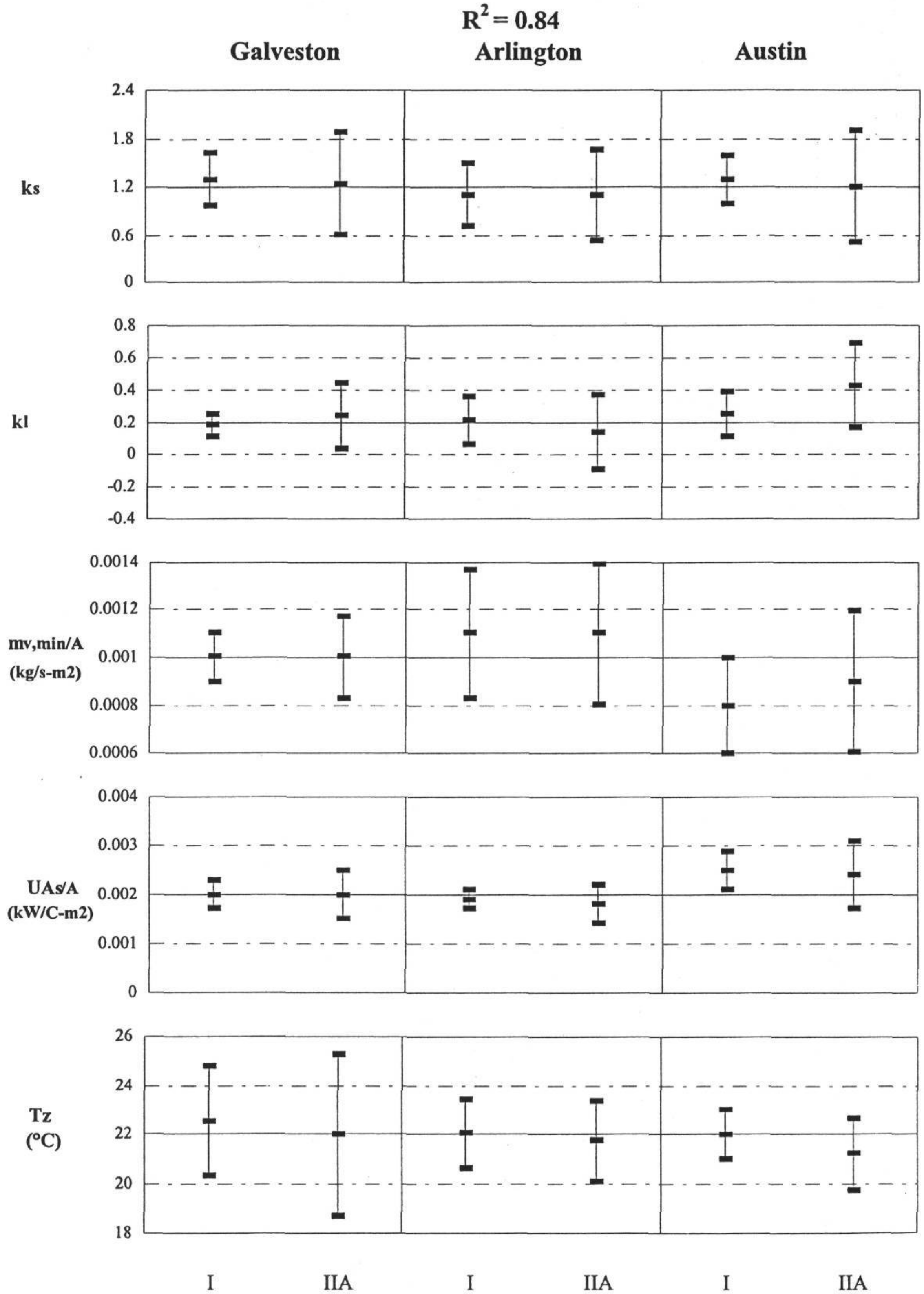

Figure A.2. Results of computer experiments with schemes of 1-step and 2-step variant A for three Texas locations estimation scheme chosen. In real world building physical parameter estimation, both sources of biases in monitored data could have very important effects on data regression results. So computer experiments carried out without putting bias into the synthetic data cannot reveal the complication and interaction of real building parameter estimation. Thus conclusion drawn from results of computer experiments in this way are superficial and misleading.

The identification schemes are still very accurate when applied to three Texas sites with different climatic behaviors, and results are present in Figure A.2, while Galveston has a more humid weather because of its seaside location, and Arlington dry climate. Here again the 1-step procedure seems the best. The reason has been discussed above same as for simulations for different R^2 levels for the WAG building at Austin.

A.3 Conclusion

In this appendix, three different parameter estimation methods discussed in chapter IV of the thesis are evaluated by the Monte Carlo approach, in order to provide insights into which estimation method is likely to minimize the confounding effect of collinearity between the regressor variables, and yield best estimates. The results obtained in this way are very different from those in chapter IV, and in fact may mislead the naive analyst. And a good regression method should be able to recognize these practical biases and try to remove them to improve identification results.

APPENDIX B

CHOICE OF DATA TIME SCALE

B.1 Introduction

The objective of this appendix is to investigate whether hourly or daily time scales are more appropriate for analyzing monitored data for the purpose of determining energy efficiency of the building. Analyzing monitored data at an hourly time scale introduces the influence of the strong diurnal schedule according to which commercial buildings are operated. Though thermal lags due to building mass do confound the analysis, it can be said that use of longer time scales progressively introduces more error in the assumption that thermodynamic minimum energy use is equal to (E_C - E_H).

Since hourly and daily monitored data normally have scattered data points due to random HVAC and building operation. We have chosen monthly time scales at which to compare results obtained by analyzing hourly or daily data. On the other hand, hourly data are more tedious to deal with than daily data. When yearly time period are selected for the analysis, use of daily data will save time and effort as compared to analysis at the hourly time scales. If daily data analysis results are close to those on an hourly bases, daily data will be preferable. The following study has been be performed to compare the monthly results calculated from hourly data and daily data separately using monitored data for two buildings.

B.2 Analysis

The same two institutional buildings as selected in the thesis are used: (a) WAG building located at the University of Texas at Austin, and (b) BUS building at University of Texas at Arlington. Both these buildings have had air-side retrofits made to them, namely the dual-duct constant air volume systems have been converted to variable air volume operation. Key characteristics of both buildings and their air handling systems have been presented in chapter V. In this study, one year of post-retrofit data has been selected for analysis, namely December 1991 to November 1992 for BUS building and August 1992 to July 1993 for WAG building. These post-retrofit data are from the LoanSTAR database which have been secured for data quality.

B.2.2 Process Equation

If $E_{C,h}$ and $E_{H,h}$ are the hourly monitored values of cooling and heating energy use, the thermodynamic minimum, i.e., ideal, one-zone building loads can be determined as:

$$Q_{B,1\text{-zone},h} = (E_{C,h} - E_{H,h}) \tag{B.1}$$

Cooling and heating energy use of the ideal, one-zone building on an hourly time scale are given by

$$E_{C,1\text{-zone},h} = Q_{B,1\text{-zone},h} \qquad \text{when } E_{C,h} > E_{H,h} \tag{B.2a}$$

and $$E_{H,1\text{-zone},h} = Q_{B,1\text{-zone},h} \qquad \text{otherwise} \tag{B.2b}$$

Subsequently, the monthly cooling and heating energy use of the ideal one-zone building based on data monitored at an hourly time scale are

$$E^{*}_{C,1\text{-zone}} = \sum_{N}\sum_{24} E_{C,1-zone,h} \tag{B.3a}$$

$$E^{*}_{H,1\text{-zone}} = \sum_{N}\sum_{24} E_{H,1-zone,h} \tag{B.3b}$$

where N is the number of days in the month.

Similarly, cooling and heating energy use based on daily time scales d have been computed as follows:

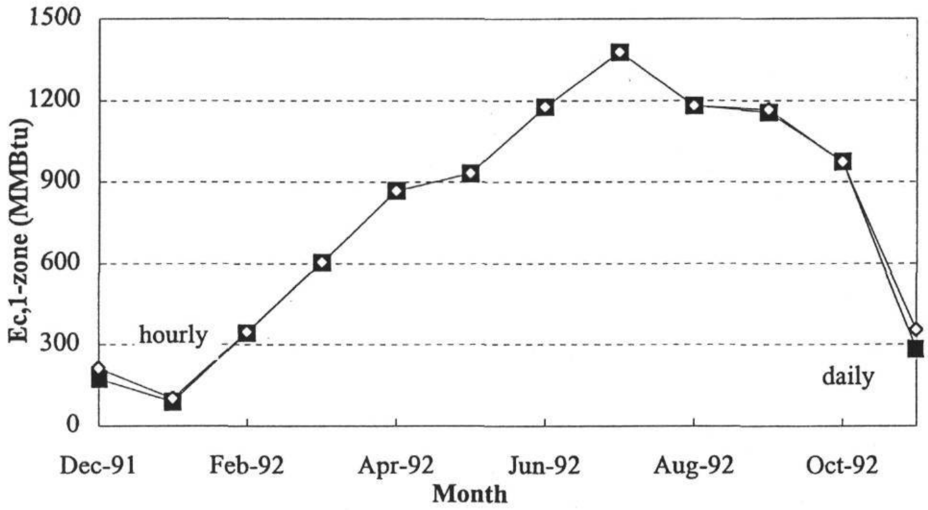

Figure B.1 Comparison of monthly cooling results based on hourly and daily data for BUS buildings

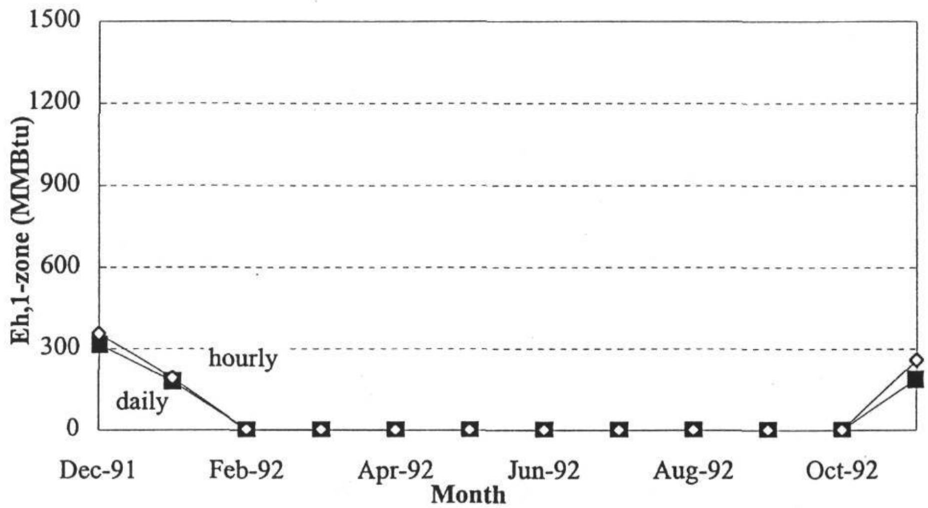

Figure B.2 Comparison of monthly heating results based on hourly and daily data for BUS buildings

$$Q_{B,1\text{-zone},d} = \sum_{24} E_{C,h} - \sum_{24} E_{H,h} \tag{B.4}$$

$$E_{C,1\text{-zone},d} = Q_{B,1\text{-zone},d} \qquad \text{when } Q_{B,1\text{-zone}} > 0 \tag{B.5a}$$

and $E_{H,1\text{-zone},d} = Q_{B,1\text{-zone},d}$ otherwise

(B.5b)Finally,

$$E_{C,1\text{-zone}} = \sum_{N} E_{C,1-zone,d} \tag{B.6a}$$

and $$E_{H,1\text{-zone}} = \sum_{N} E_{H,1-zone,d} \tag{B.6b}$$

B.3 Discussion of Results and Conclusions

Figure B.1 and B.2 depict the difference in the values of the monthly total idealized cooling requirements $E_{C,1\text{-zone}}$ and $E^*_{C,1\text{-zone}}$ based on idealized daily and hourly values respectively on one hand, and corresponding idealized heating requirements $E_{H,1\text{-zone}}$ and $E^*_{H,1\text{-zone}}$ on the other, for both the BUS and the WAG buildings. It is noted that, except for the months of November to March during when there is a very small difference between the aggregated hourly and daily values, ideal cooling and heating loads based on hourly or daily data are identical. Even during the winter months, the

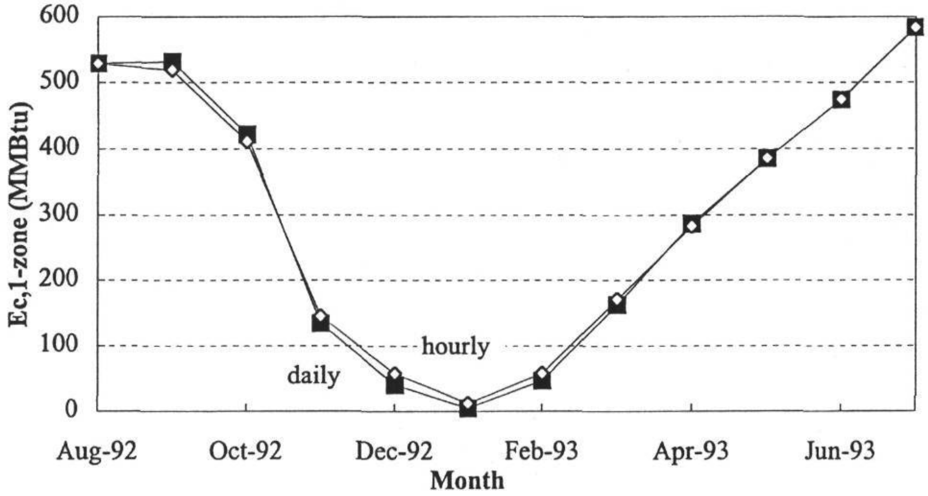

Figure B.3 Comparison of monthly cooling results based on hourly and daily data for WAG buildings

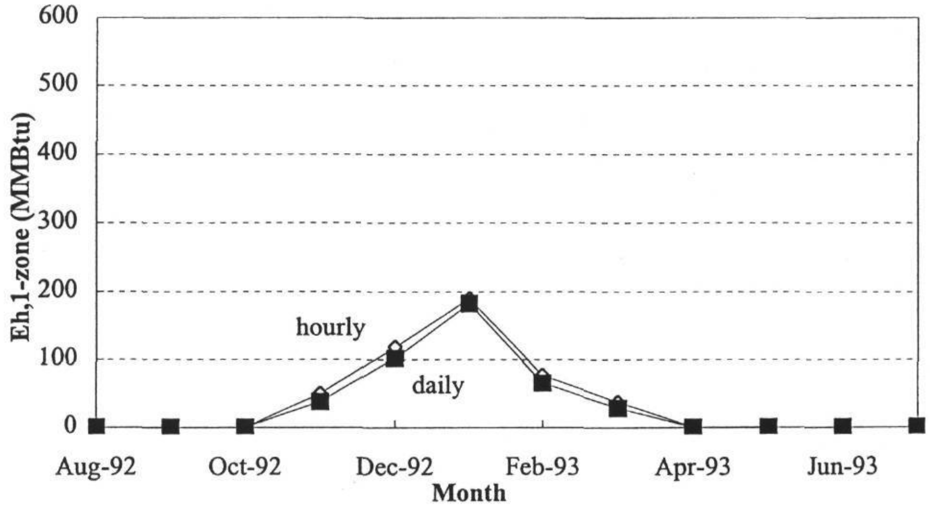

Figure B.4 Comparison of monthly heating results based on hourly and daily data for WAG buildings differences between the loads based on hourly and daily data are small. Hence, in the analysis performed in the thesis, daily time scales have been adopted.

VITA

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